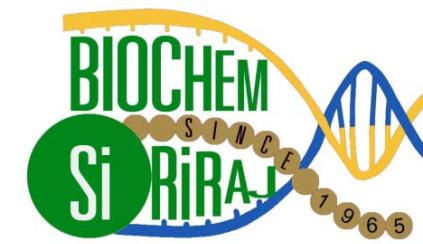




Mahidol University



Metabolomics and its application

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Faculty of Medicine Siriraj Hospital, Mahidol University

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Learning objectives

1. Introduction to Metabolomics

- Metabolomics ?
- Relation to other –omics →systems biology

2. Metabolomics technologies

3. Metabolomics and its application

Metabolomics or Metabonomics ??



“Comprehensive and quantitative analysis of all metabolites...” Fiehn 2001.



“The quantitative measurement of the time-related Multi-parametric metabolic response of living Systems to pathophysiological stimuli or genetic modification” Nicholson et al., 1999

The difference: only philosophy

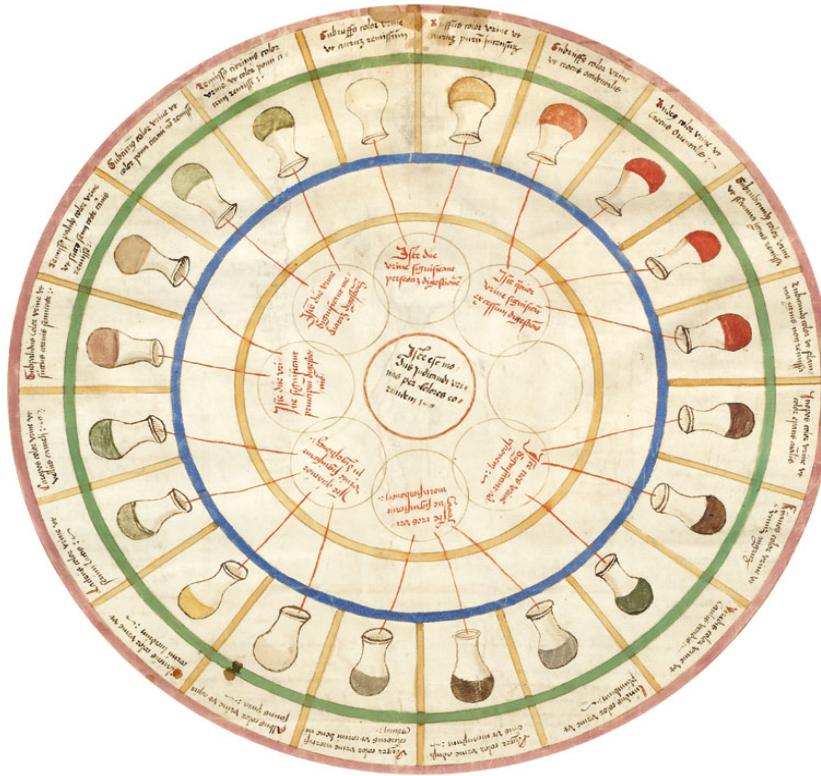
Metabolomics aims to characterize and quantify all small molecules in a sample

Metabonomics aims to measure global dynamic metabolic response of living systems

The terms are often used interchangeably, analytical and modeling procedure are the same

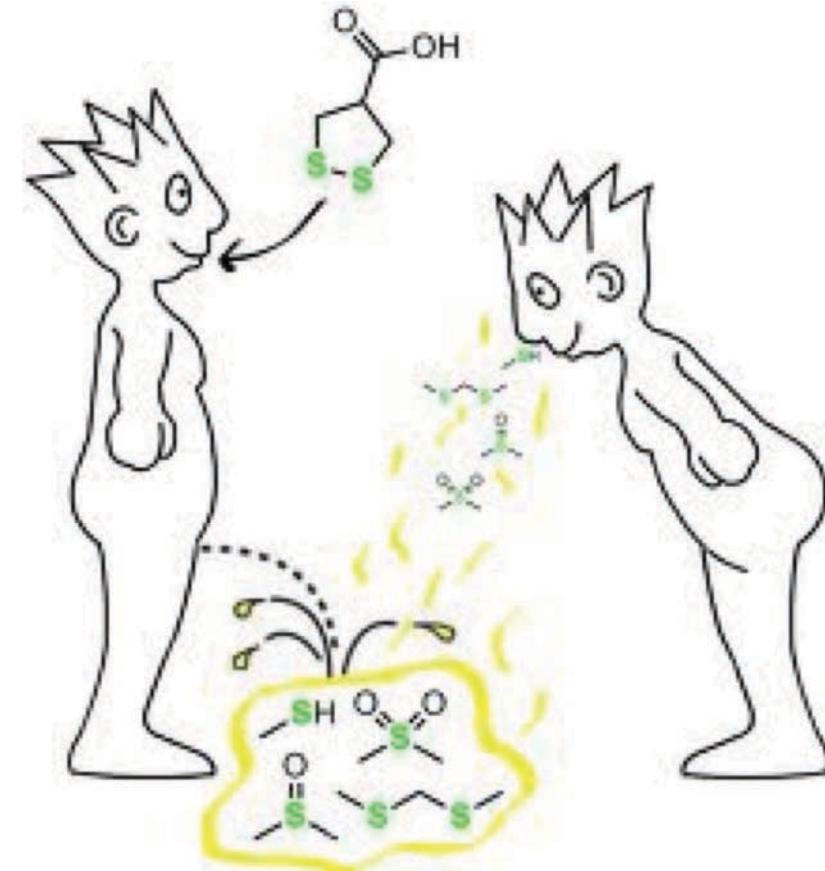
Metabolomics in clinical research

The idea that changes in tissues or biological fluid are indicators of disease goes back at least as far back as ancient Greece.



Metabonomics of yore

This urine wheel describes the possible colors, smells, test of urine and uses them to diagnose disease.



History and development

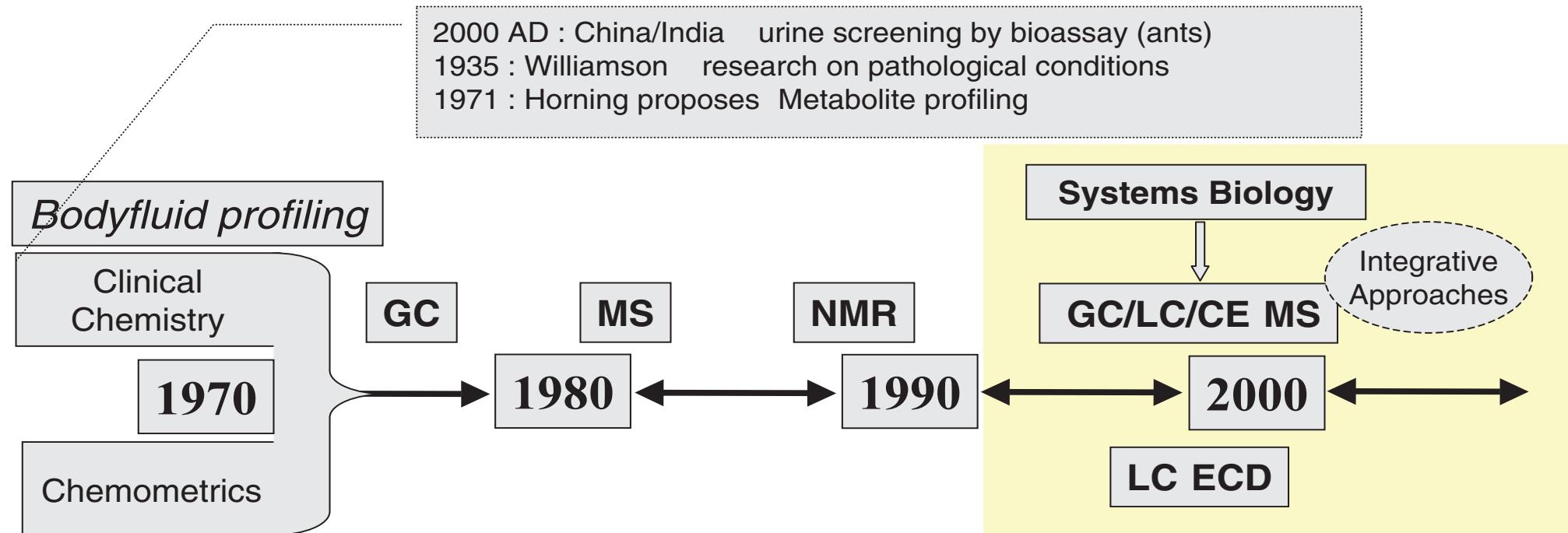
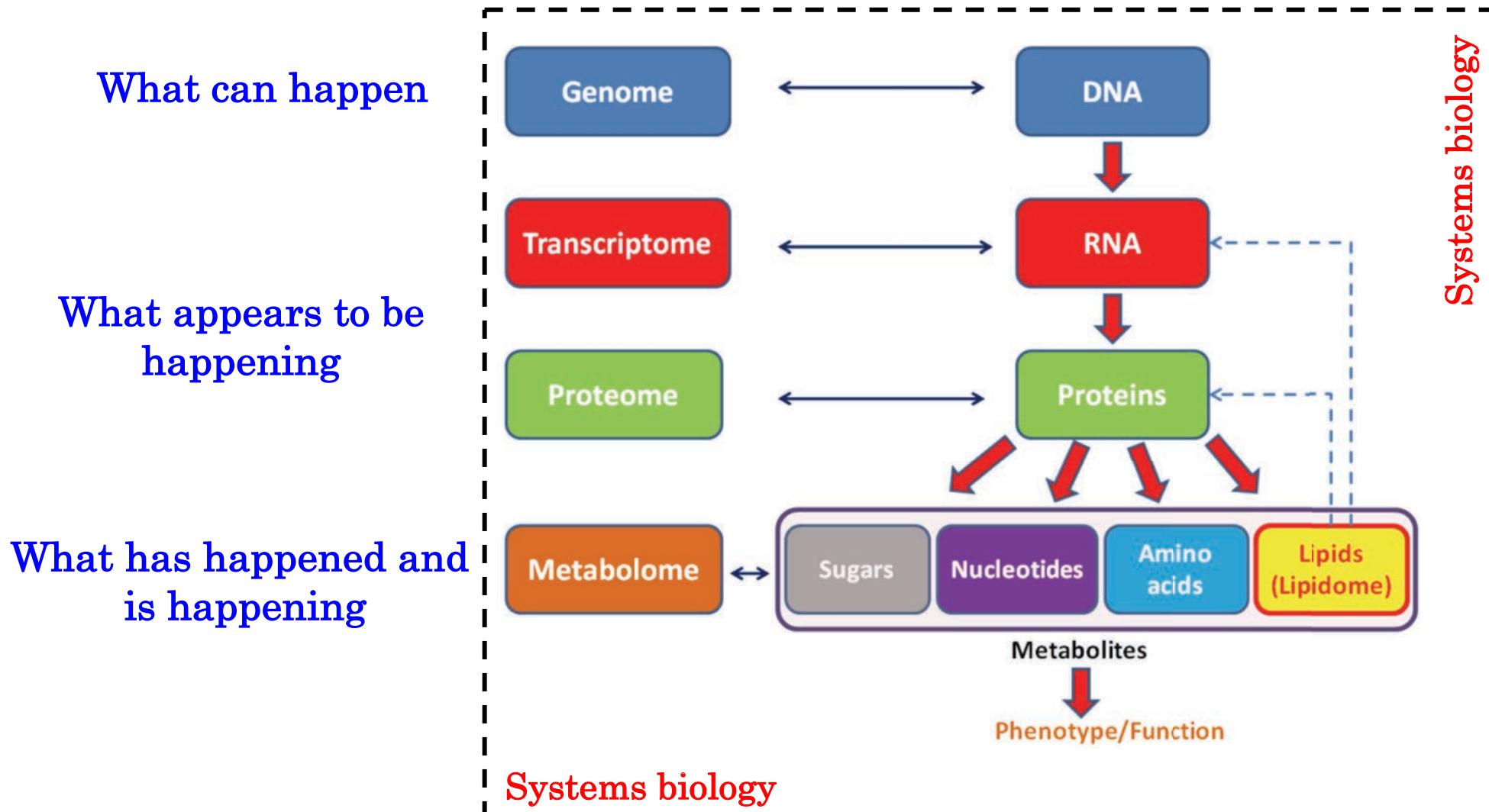


Figure 2. Body fluid profiling. Integration of chemometrics and analytical technologies in biomedical research.

AD = Anno Domini

Metabolomics & other omics



Systems Biology

It is a biology-based interdisciplinary field of study that focuses on complex interactions within biological systems, using a holistic approach



"Systems biology...is about putting together rather than taking apart, integration rather than reduction. It requires that we develop ways of thinking about integration that are as rigorous as our reductionist programmes, but different....It means changing our philosophy, in the full sense of the term" ([Denis Noble](#))

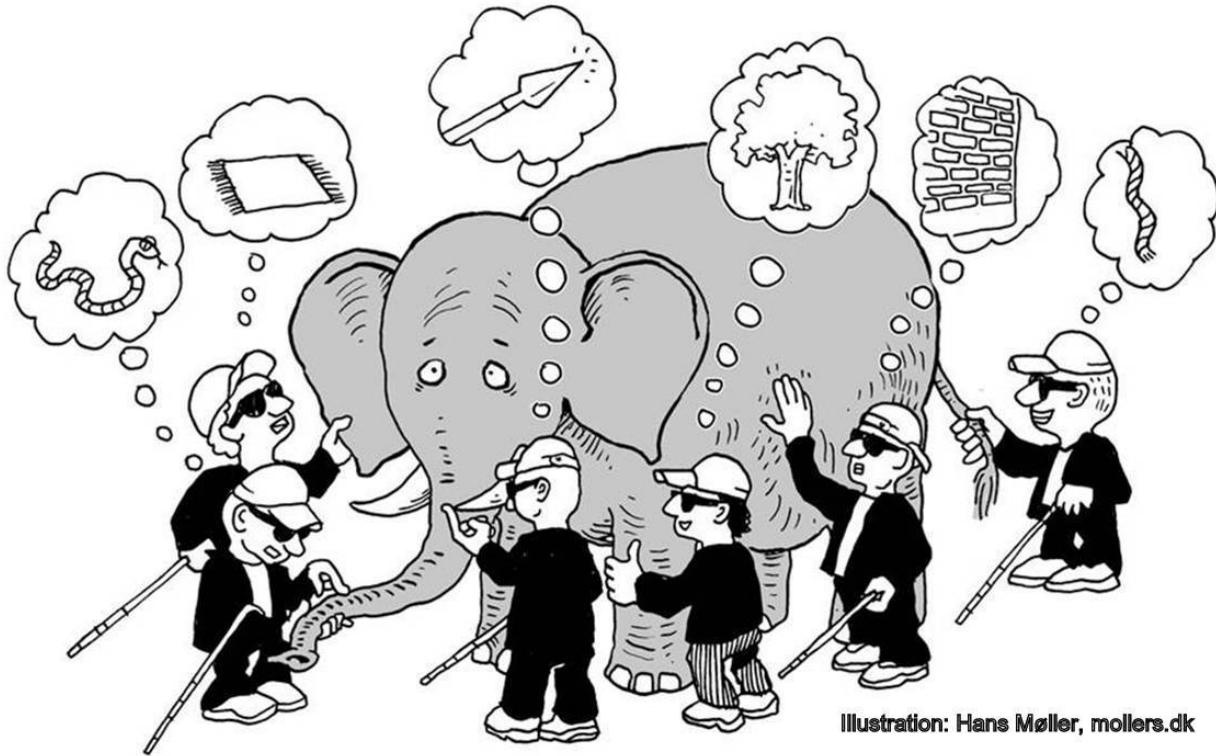


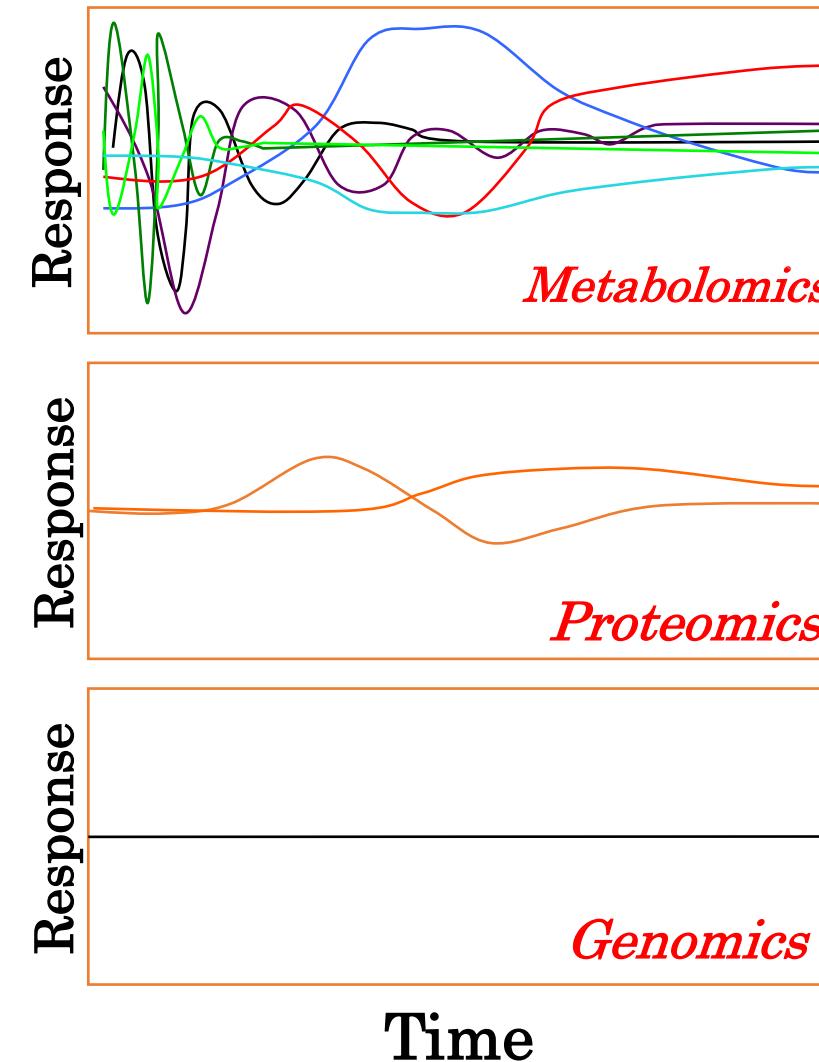
Illustration: Hans Møller, [mollers.dk](#)

The six blind men and the elephant

Metabolomics provides a good sensitivity for quantifying phenotype



Normal Stress



Terms

Metabolites: intermediates and products of metabolism (MW <1k Da)
e.g. amino acids, organic acids, sugars, lipids...

Metabolome: a complete set of metabolites in an organism

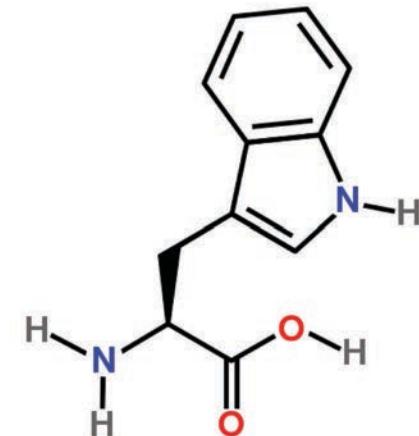
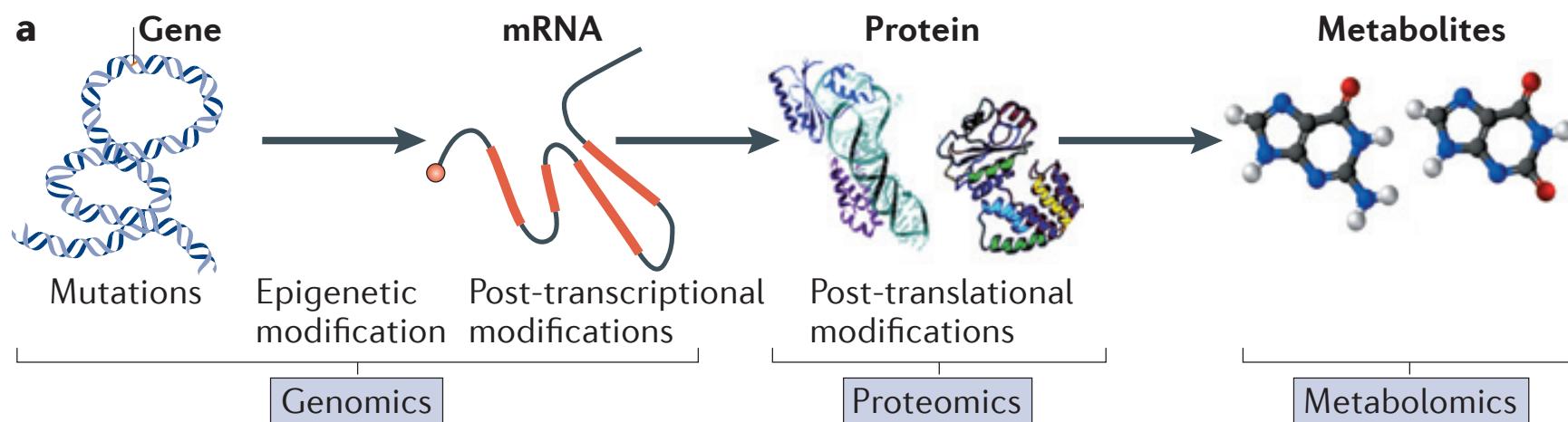
Metabolome is subdivided into endo- and exo-metabolome that cover the intra- and extra- metabolites

Targeted analysis: only the metabolites of interest

Untargeted analysis or metabolite profiling: as many as possible

What is a metabolite?

- Any organic molecule detectable in the body with a MW < 1500 Da
- Includes peptides, oligonucleotides, sugars, nucleosides, organic acids, ketones, aldehydes, amines, amino acids, lipids, steroids, alkaloids, foods, food additives, toxins, pollutants, drugs and drug metabolites
- Includes human & microbial products
- Concentration > detectable (1 pM)



Metabolites

Plant-based metabolomics:

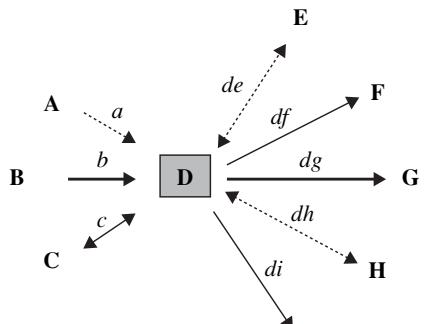
- Primary

- Secondary

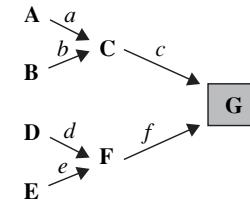
Human-based metabolomics:

- Endogenous

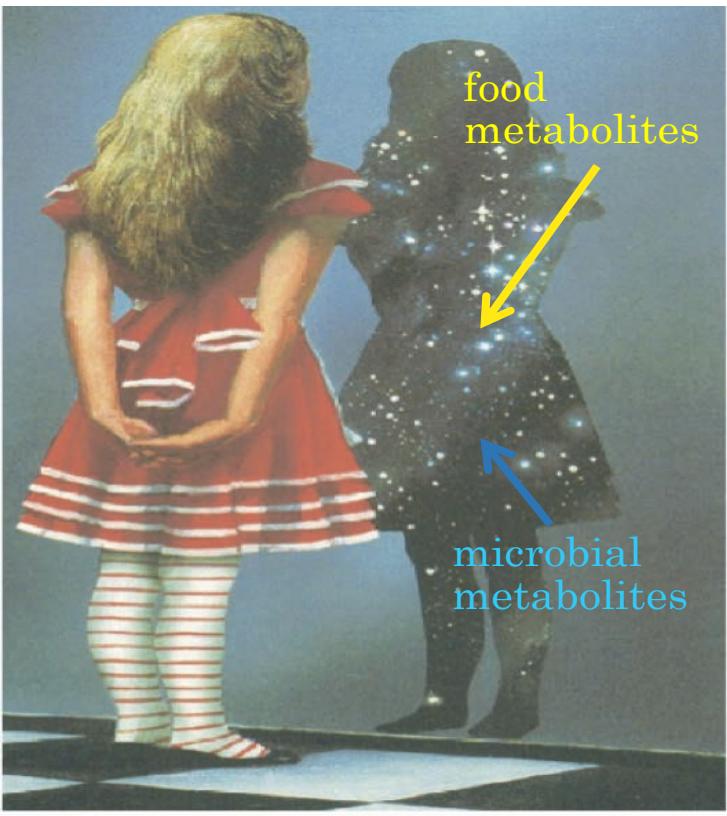
- Exogenous



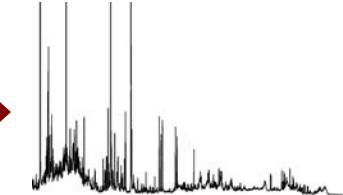
Primary metabolism



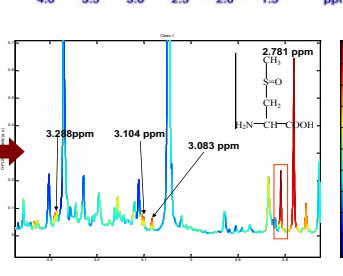
Secondary metabolism



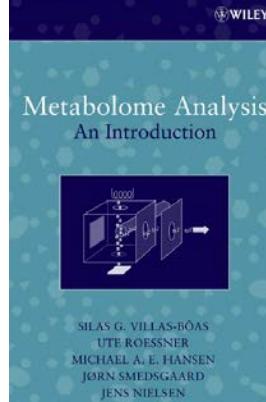
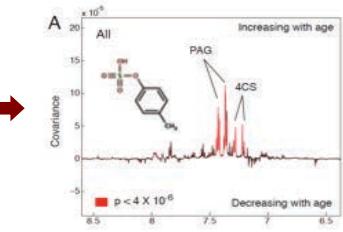
BIOFLUID METABOLITES

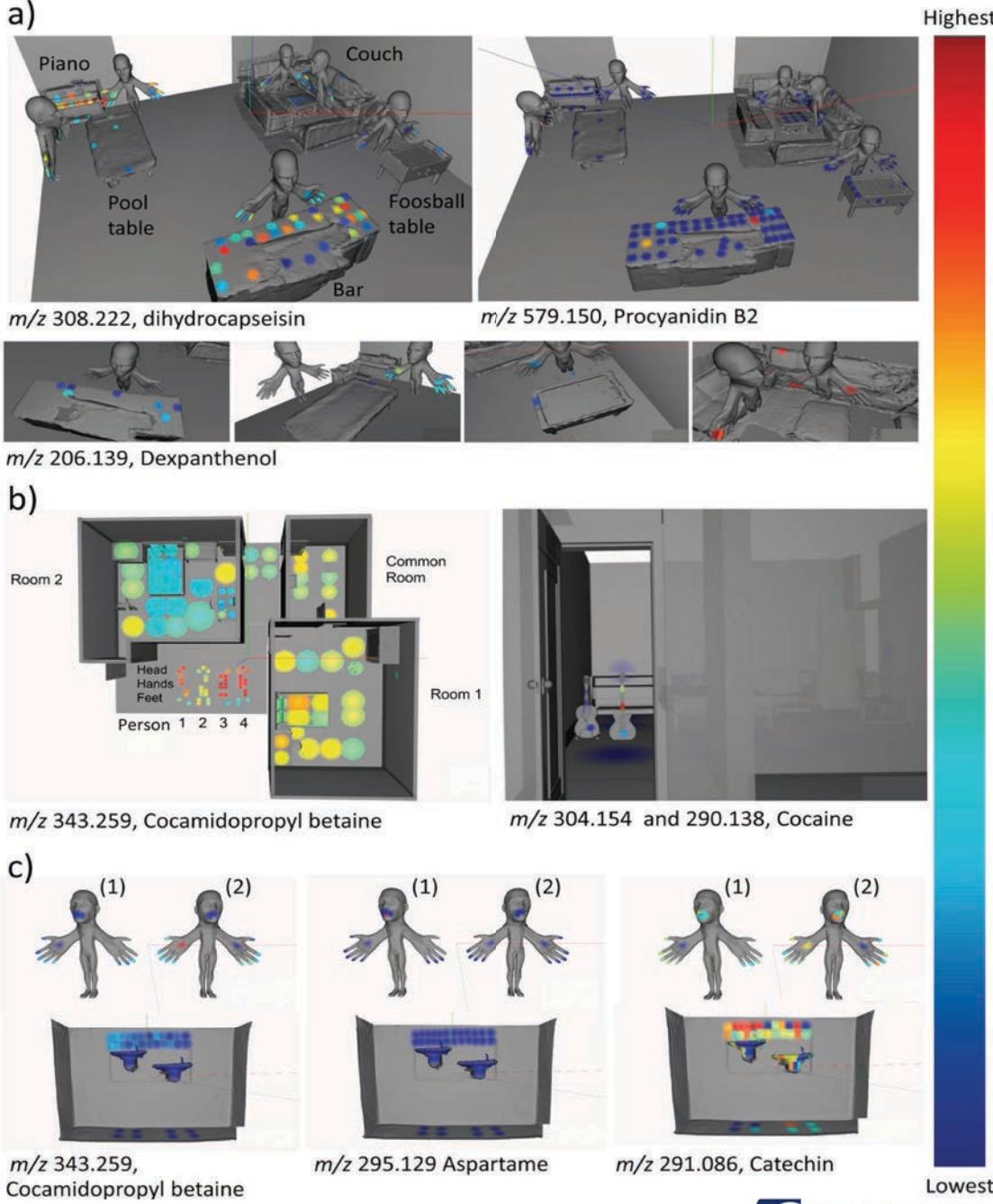
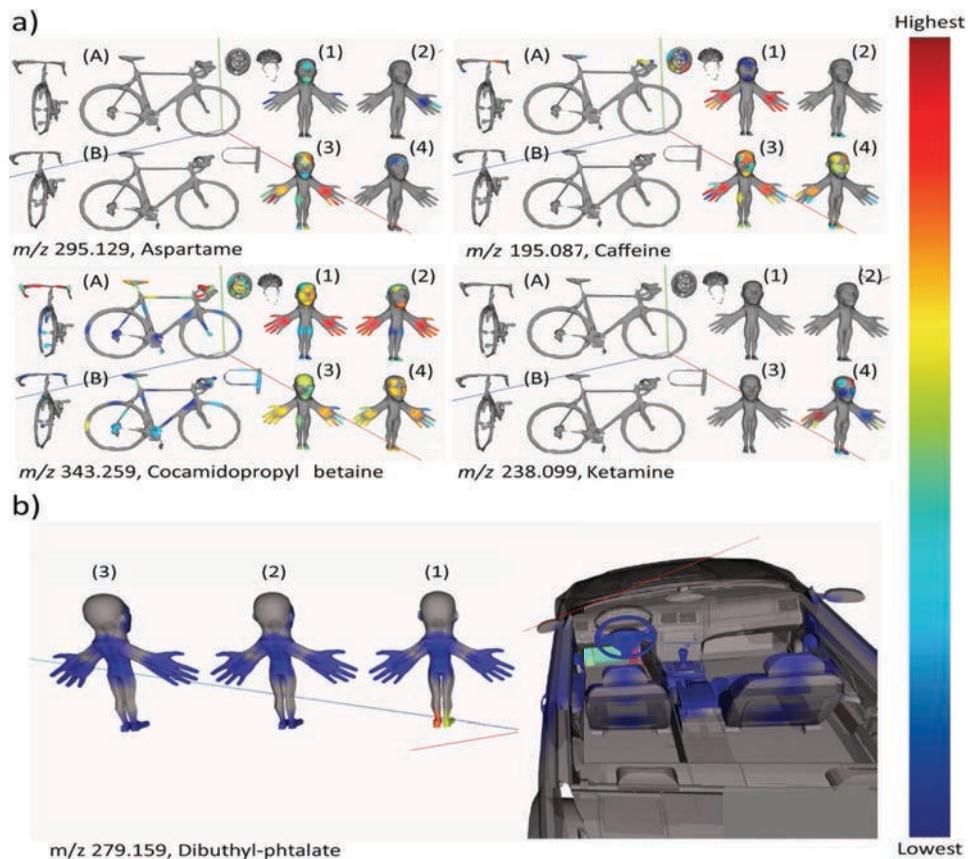
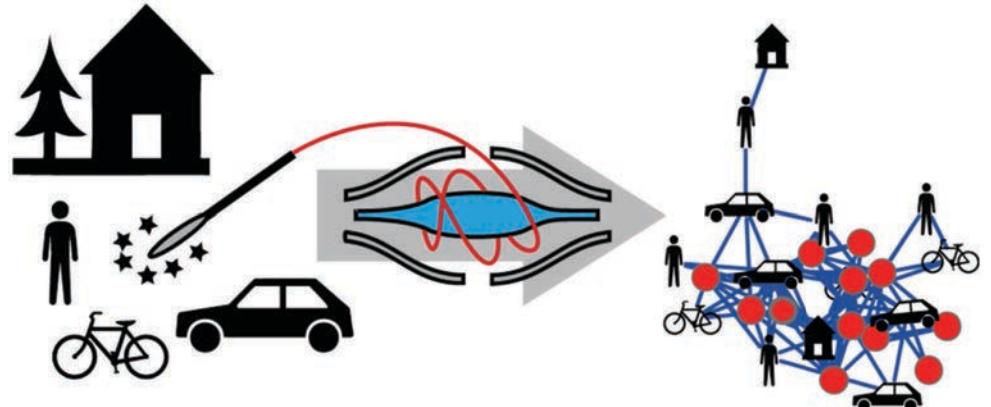


DIETARY COMPONENTS

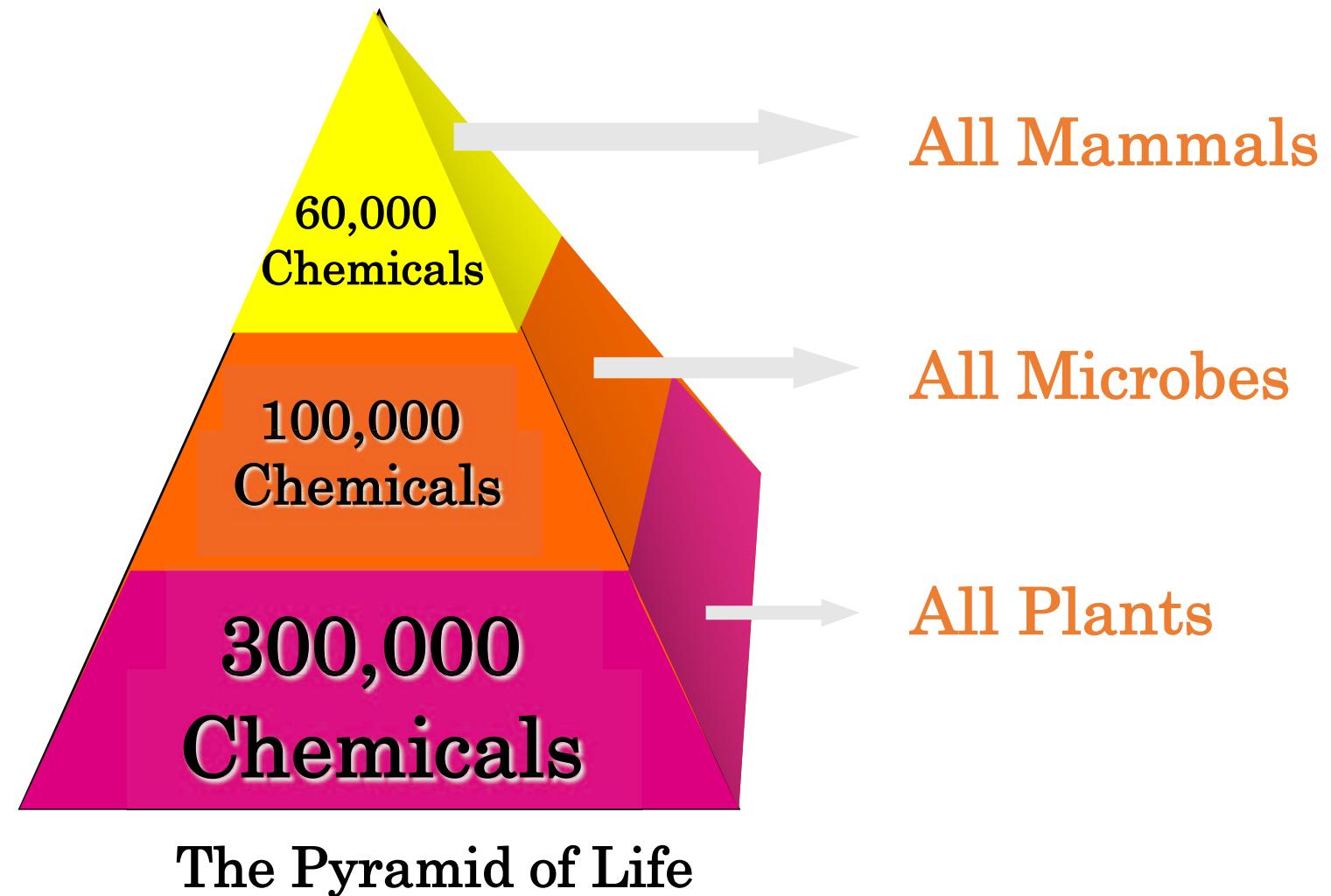


MICROBIAL METABOLITES





Different Metabolomes



Human Metabolomes (2015)

3670 (T3DB)

Toxins/Env. Chemicals

1240 (DrugBank)

Drug metabolites

28500 (FooDB)

Food additives/Phytochemicals

1550 (DrugBank)

Drugs

19700 (HMDB)

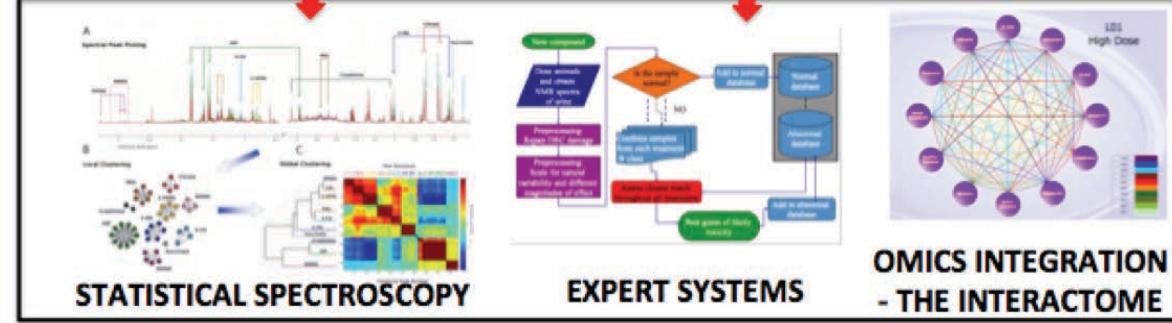
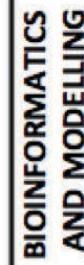
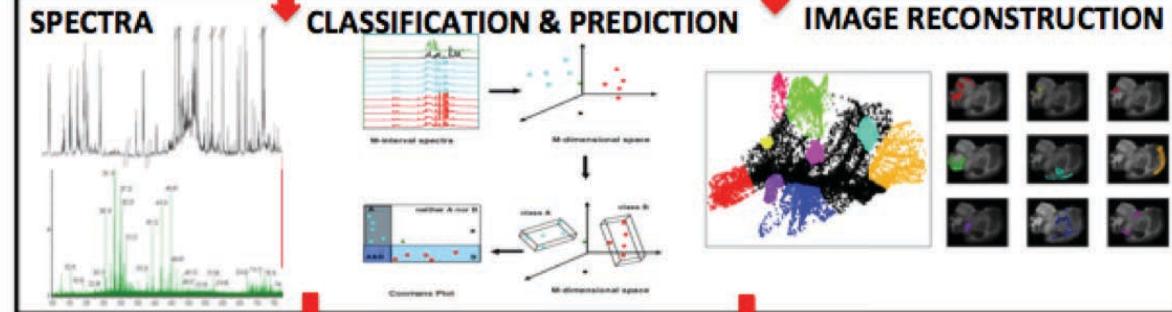
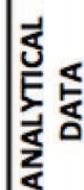
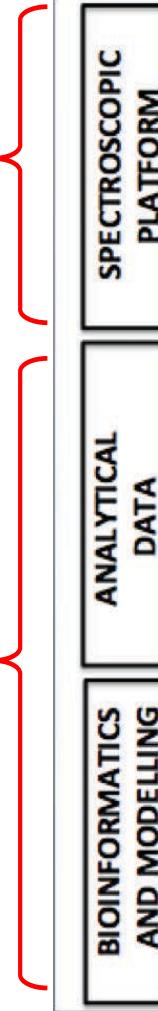
Endogenous metabolites



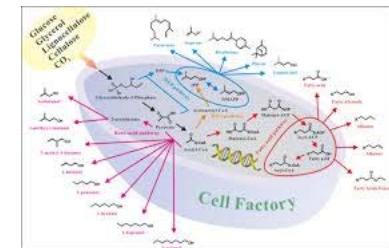
Metabolomics research



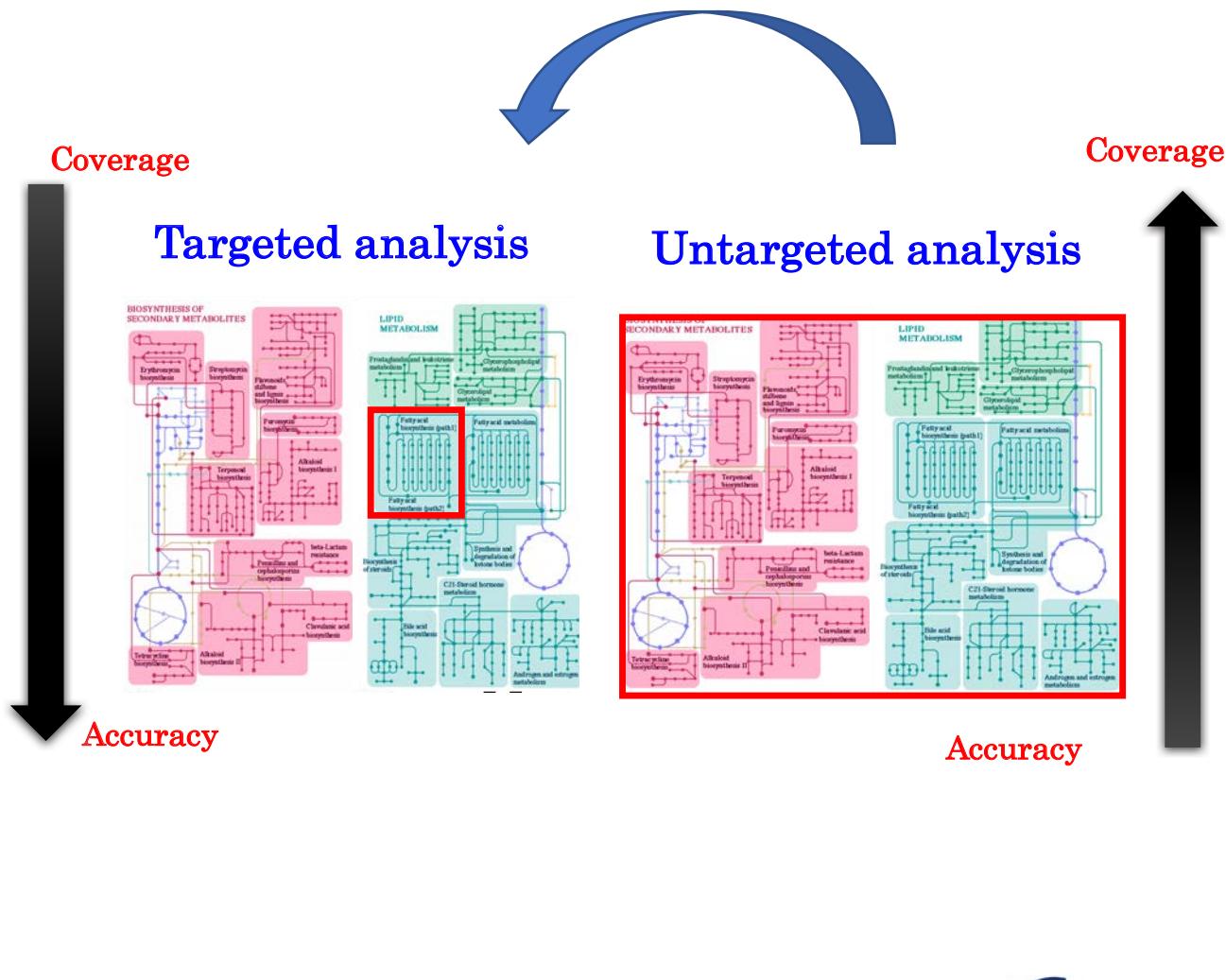
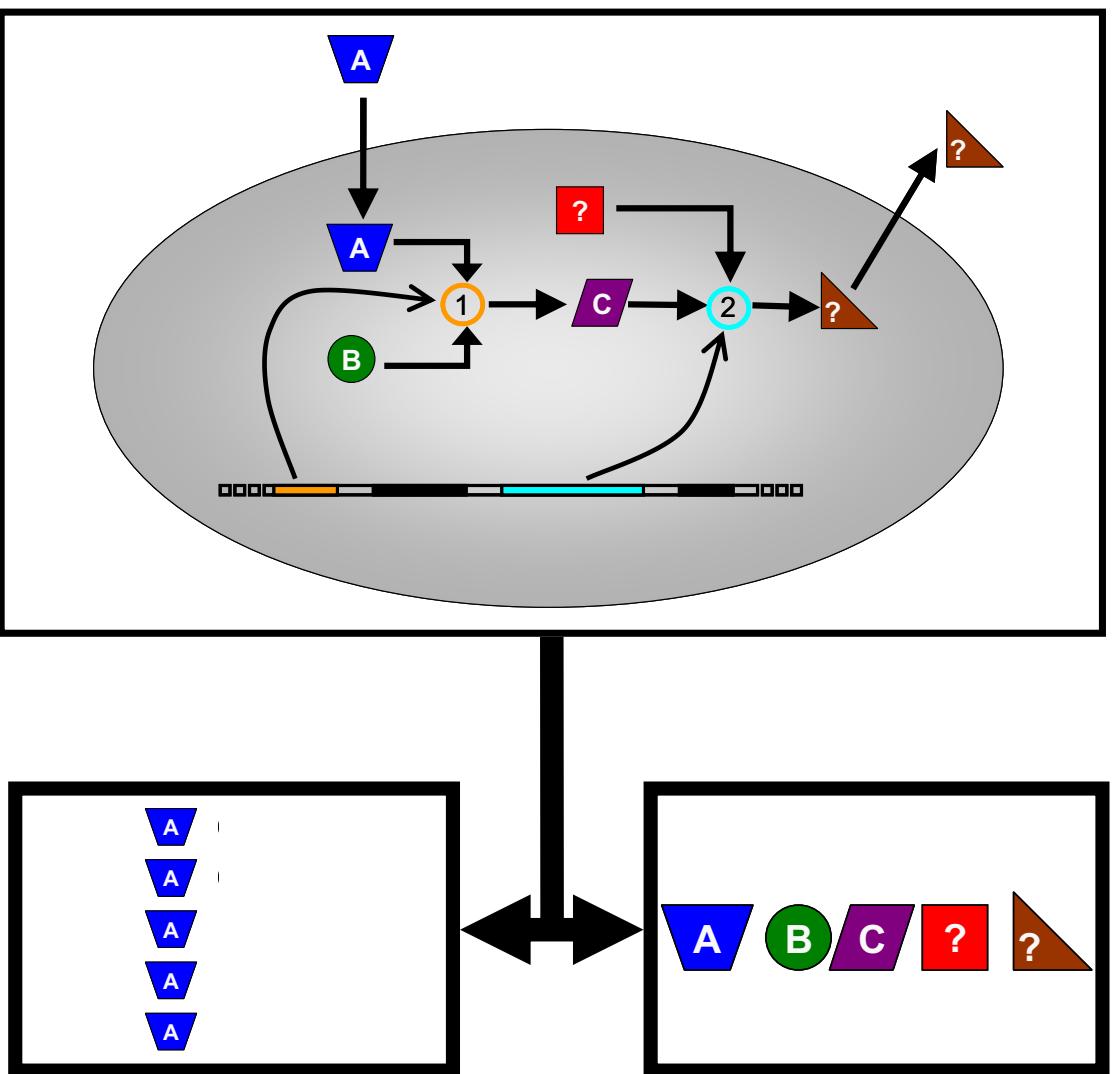
Wet chemistry



Dry chemistry



Approaches in metabolomics

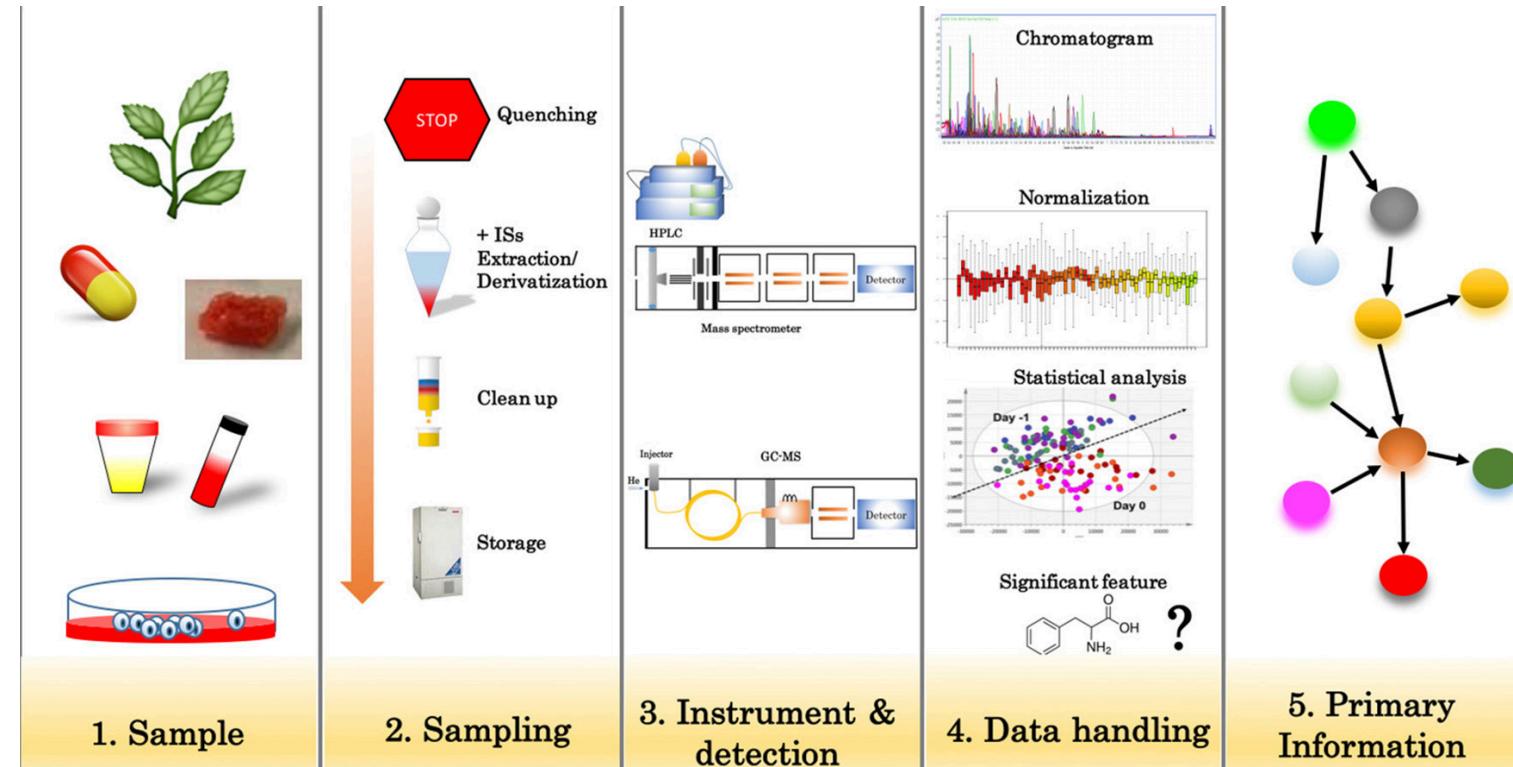


Untargeted analysis (discovery)



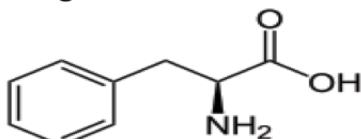
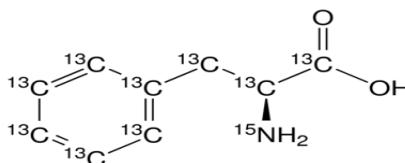
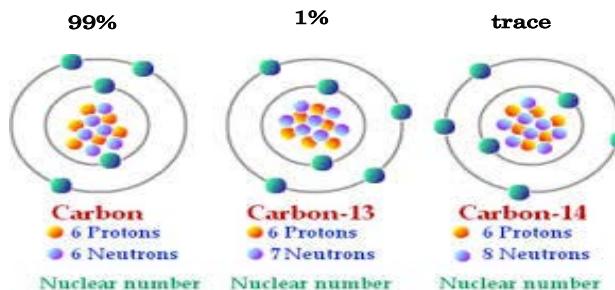
Deviation of retention time, sensitivity

- Fluctuation of room temperature
- Pressure
- Column degradation
- Sample carryover
- Mobile phase

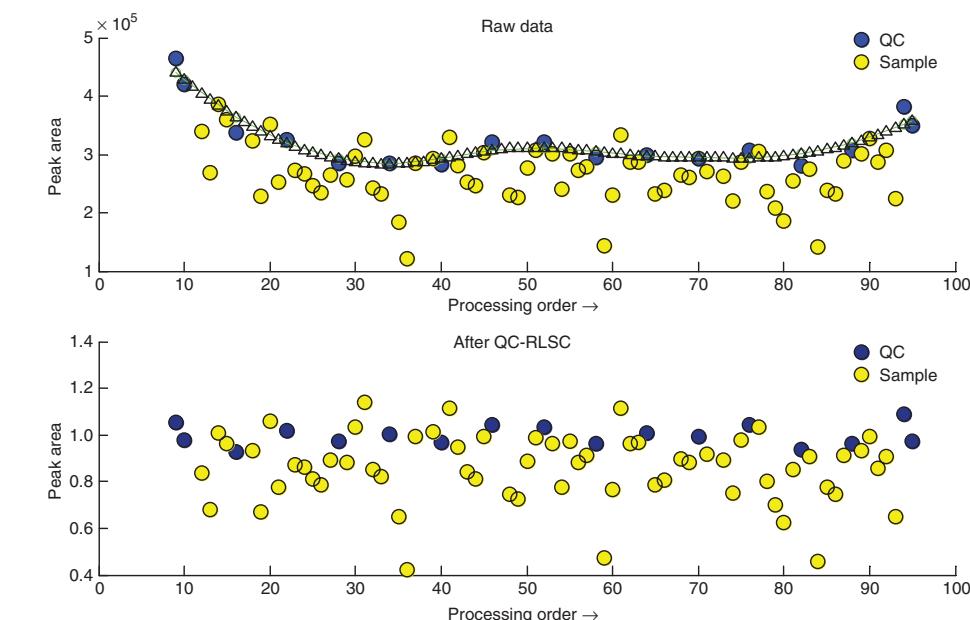
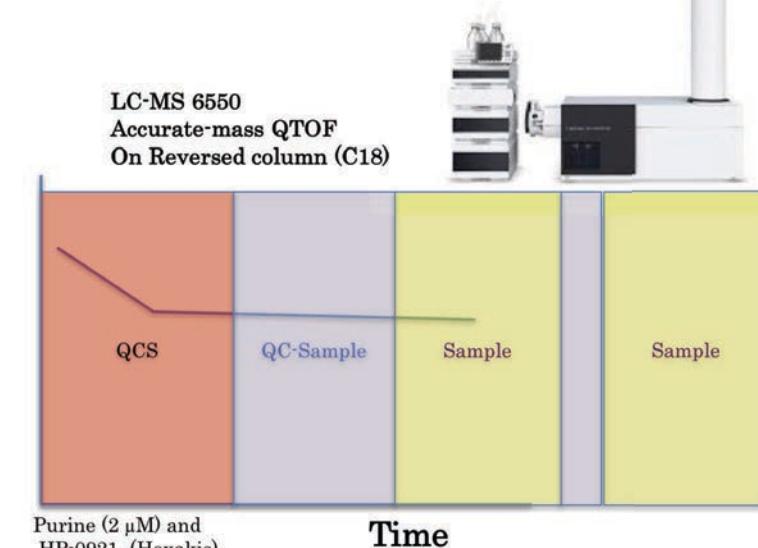


Untargeted analysis (continued)

Sample extraction
Internal standard
Pooled sample

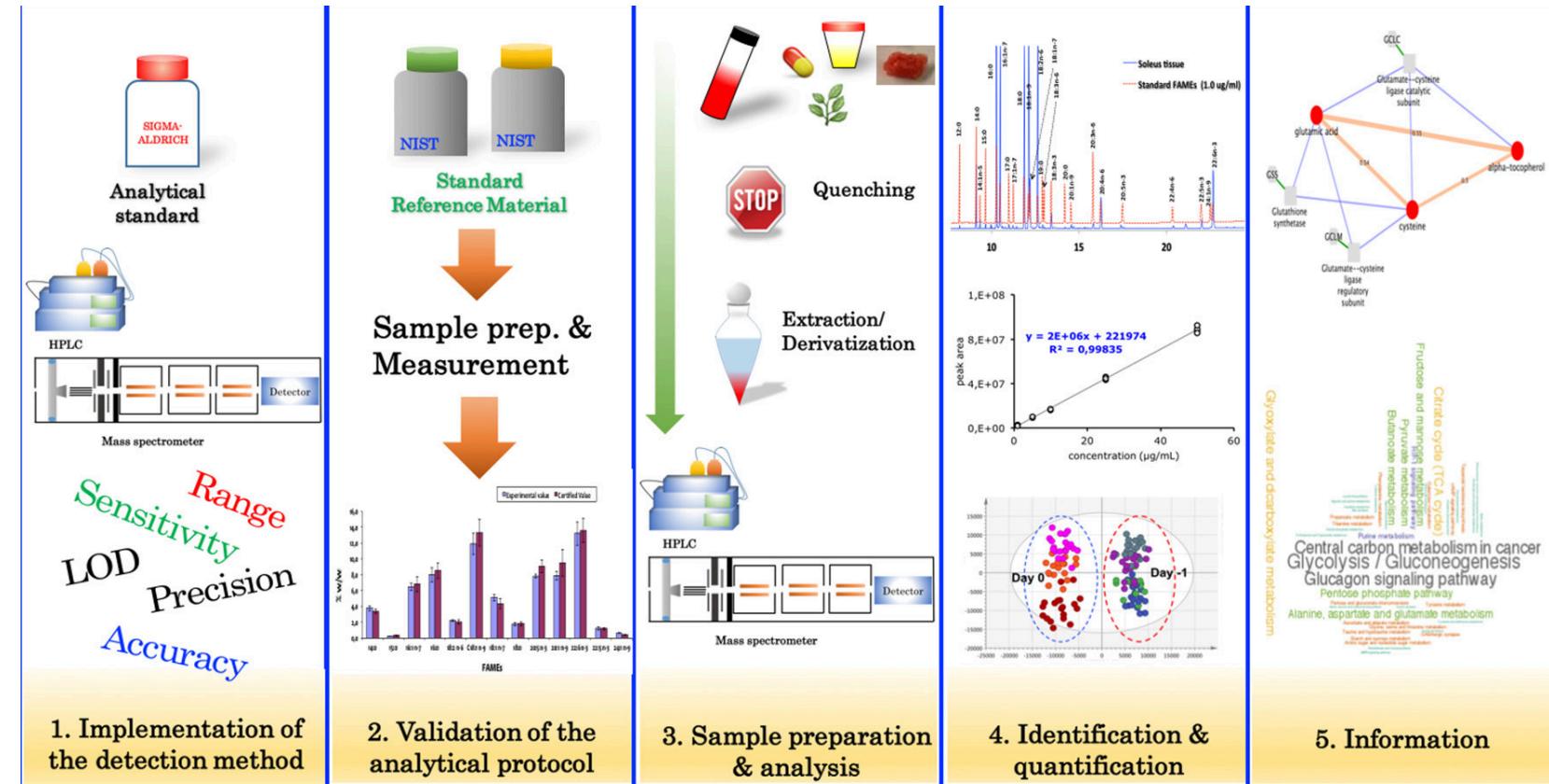


LC-MS 6550
Accurate-mass QTOF
On Reversed column (C18)

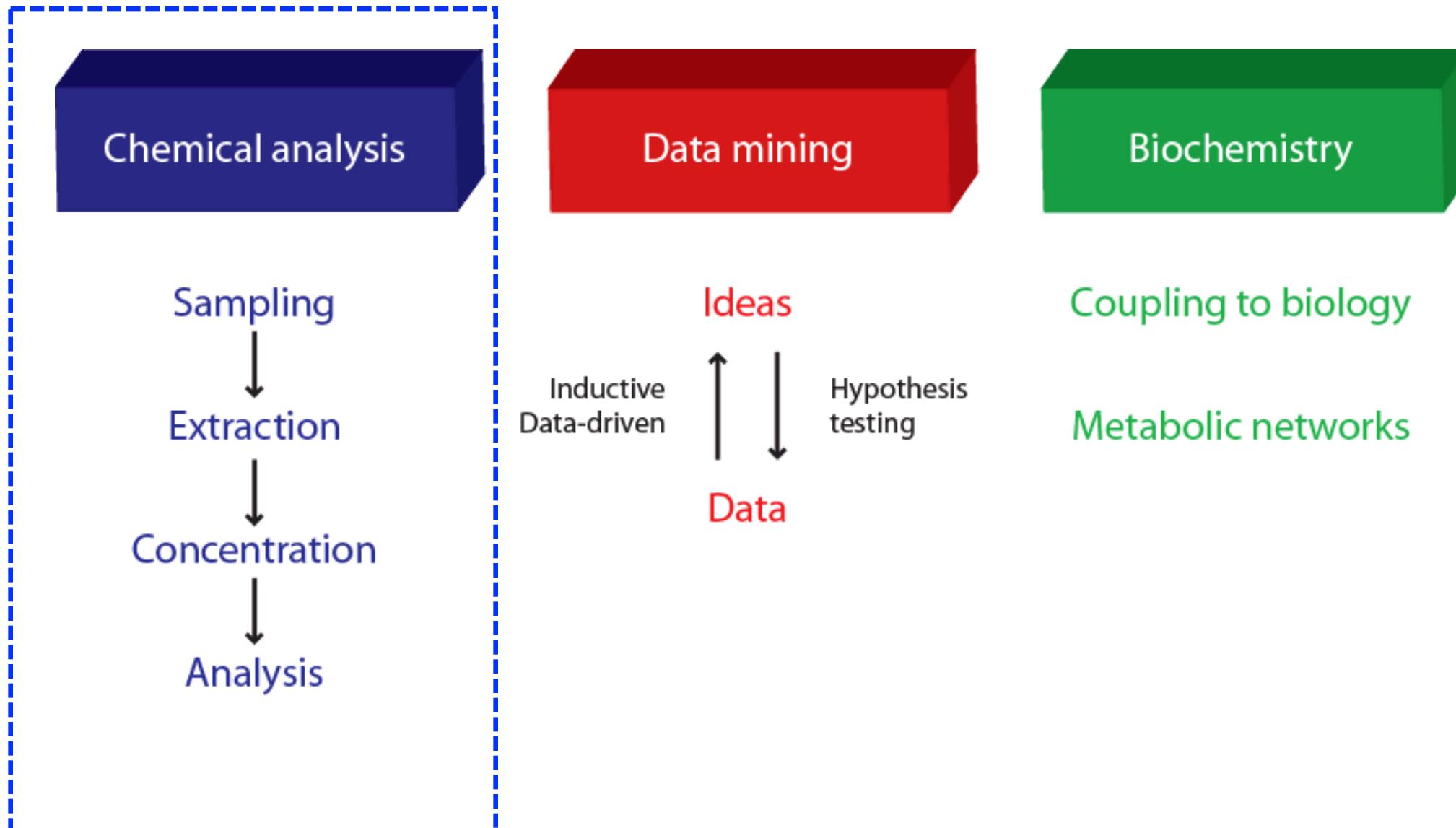


Targeted analysis (GC- or LC/MS)

- Confirm results from untargeted
- Quantitative or Qualitative
- Production for compounds of interest
- Pharmacokinetics studies
- Genetic modification on a specific enzyme



Metabolomics workflow



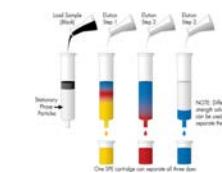
Chemical analysis (sampling & sample prep.)



Quenching



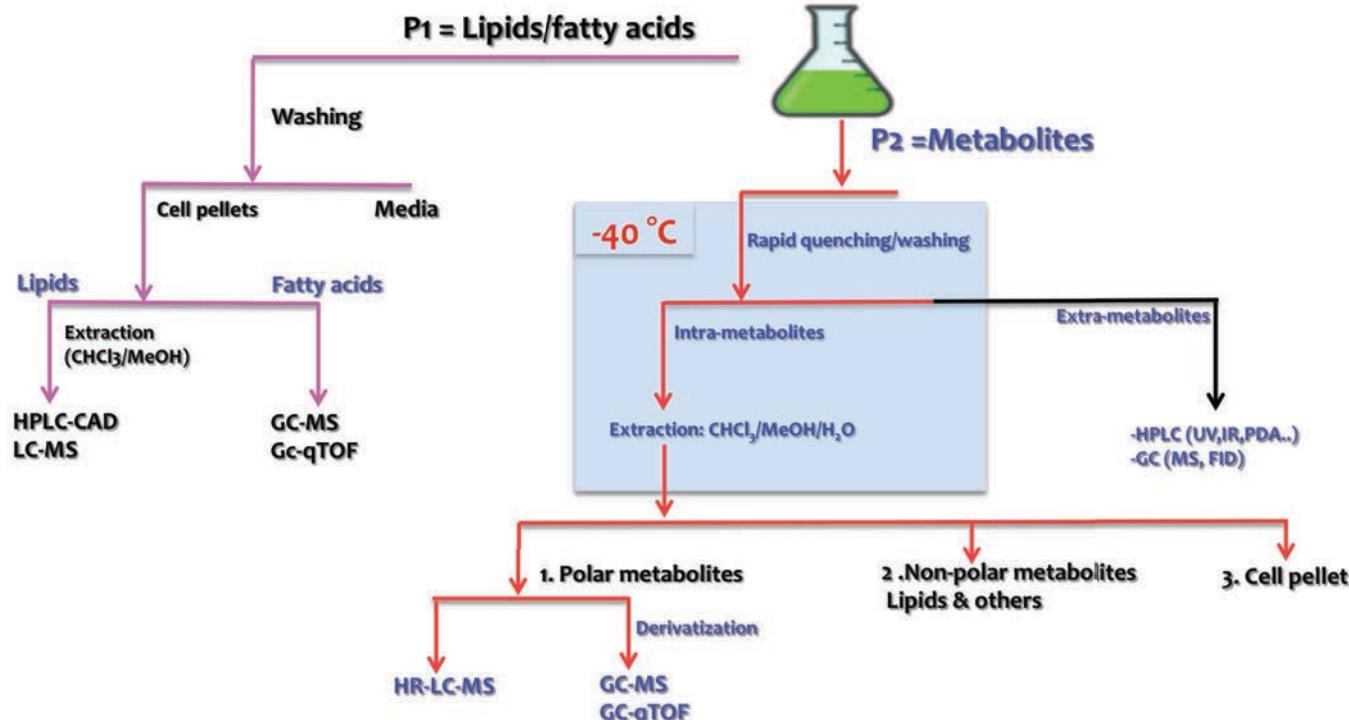
Extraction



Clean up/conc./Derivatization



Storage

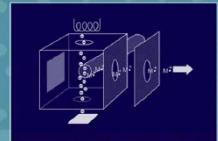


Analysis

Why quenching

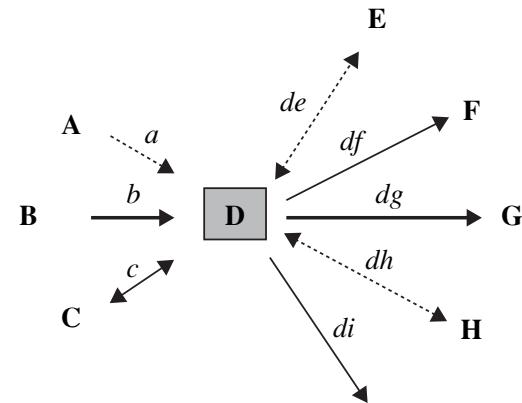
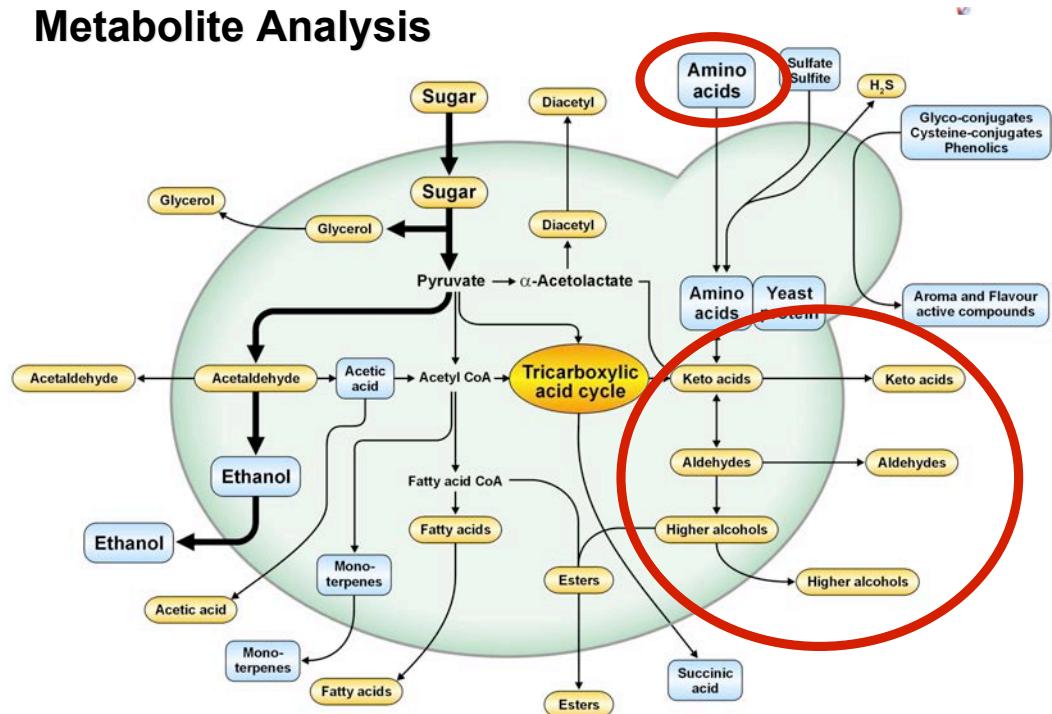
- Intracellular turnover
- Primary metabolite: metabolite that related to biochemical reaction
- Second metabolites: not used for the growth, secreted, or accumulated in the cell
- Extracellular turnover
- Secreted metabolites

Metabolome Analysis
An Introduction

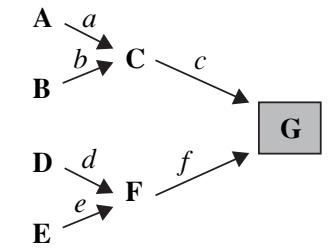


SILAS G. VILLAS-BOAS
UTE ROESSNER
MICHAEL A. E. HANSEN
JØRN SMEDSGAARD
JENS NIELSEN

Metabolite Analysis



Primary metabolism

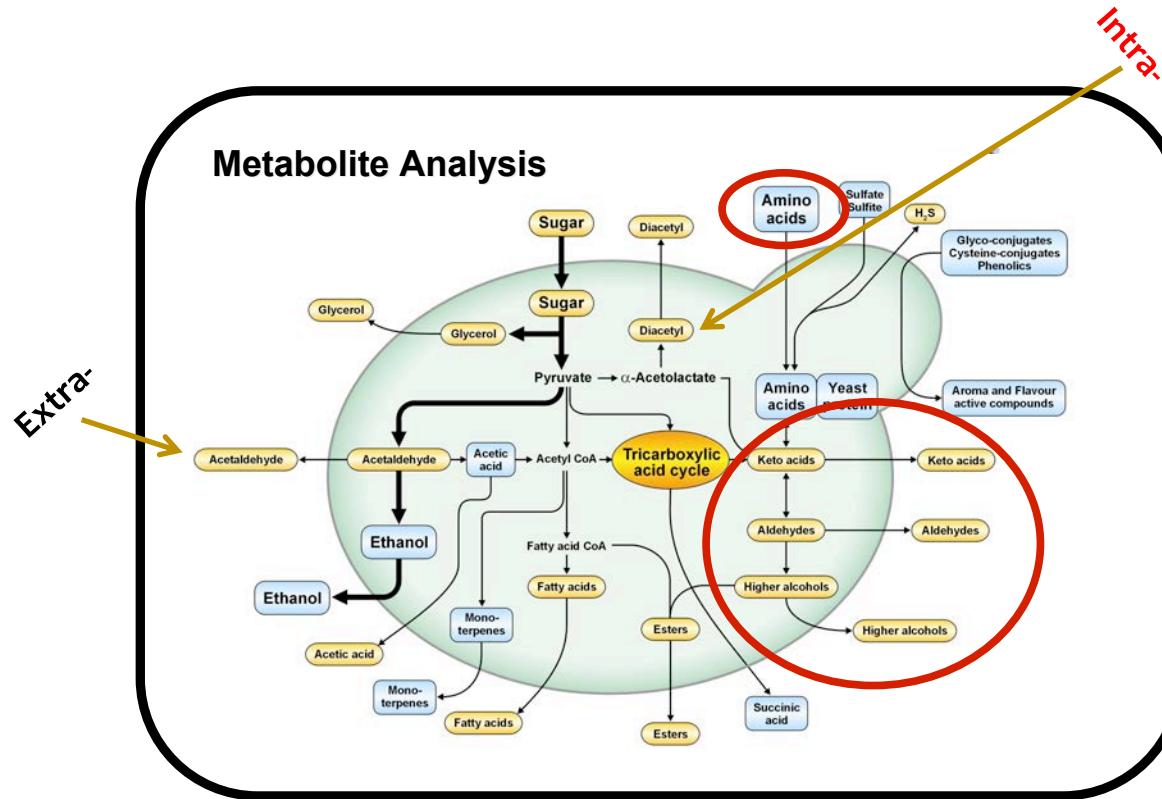


Secondary metabolism

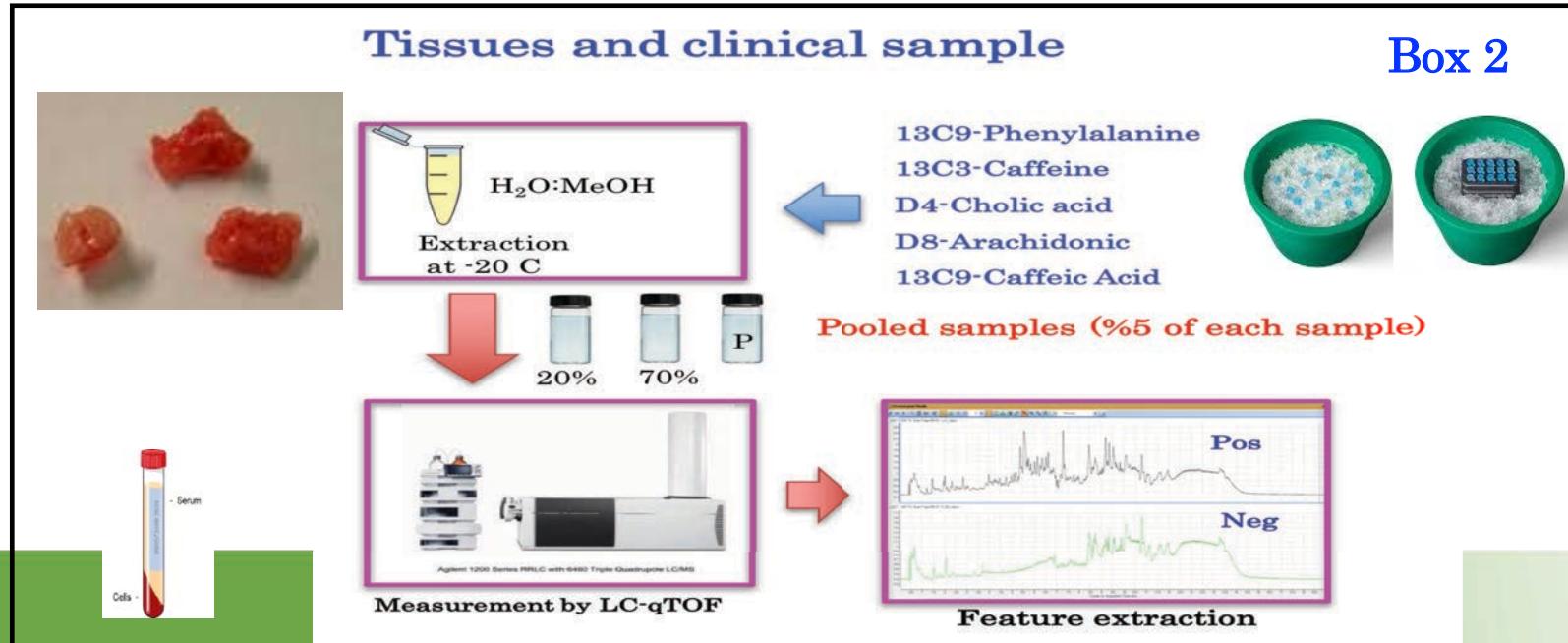
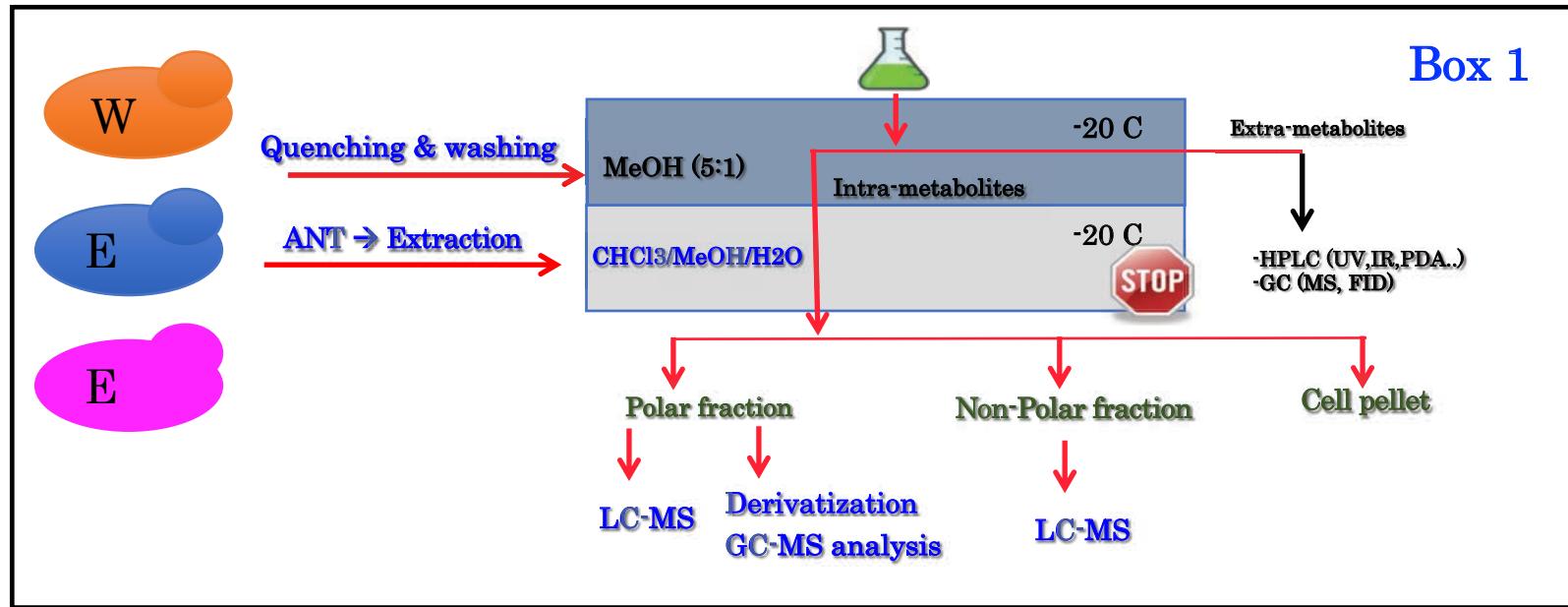
Quenching and washing (Metabolite)

The purpose of quenching is to rapidly stop metabolism and Prevent change of metabolites

- Fast filtration and washing the cell with MEOH at -40 °C
- Cold method quenching at -40 °C

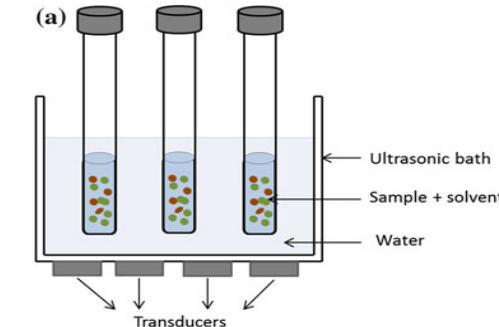
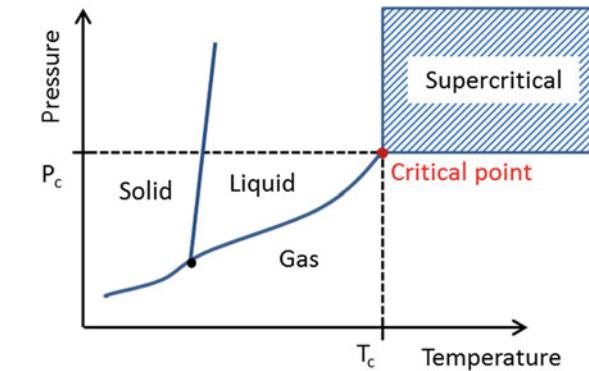
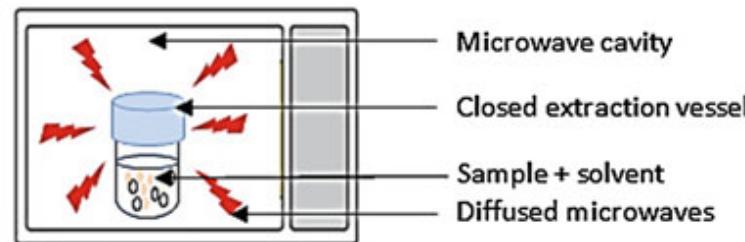
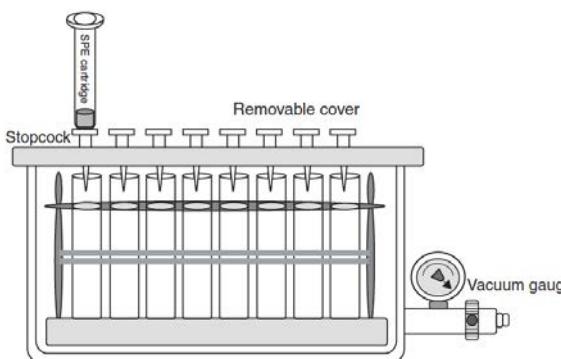
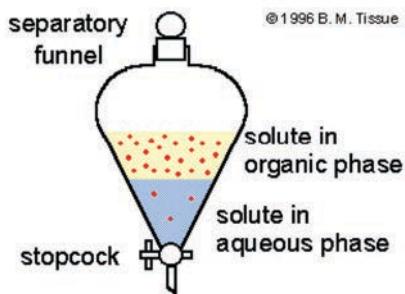


When is a good time for the internal standards



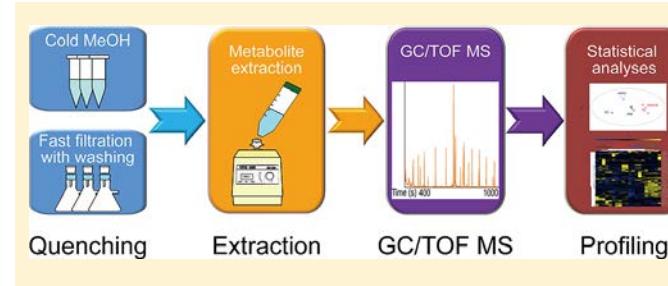
Extraction

- Liquid-liquid extraction
- Solid-phase Extraction (SPE)
- Super critical fluid extraction
- Ultrasound Extraction
- Microwave-assisted extraction

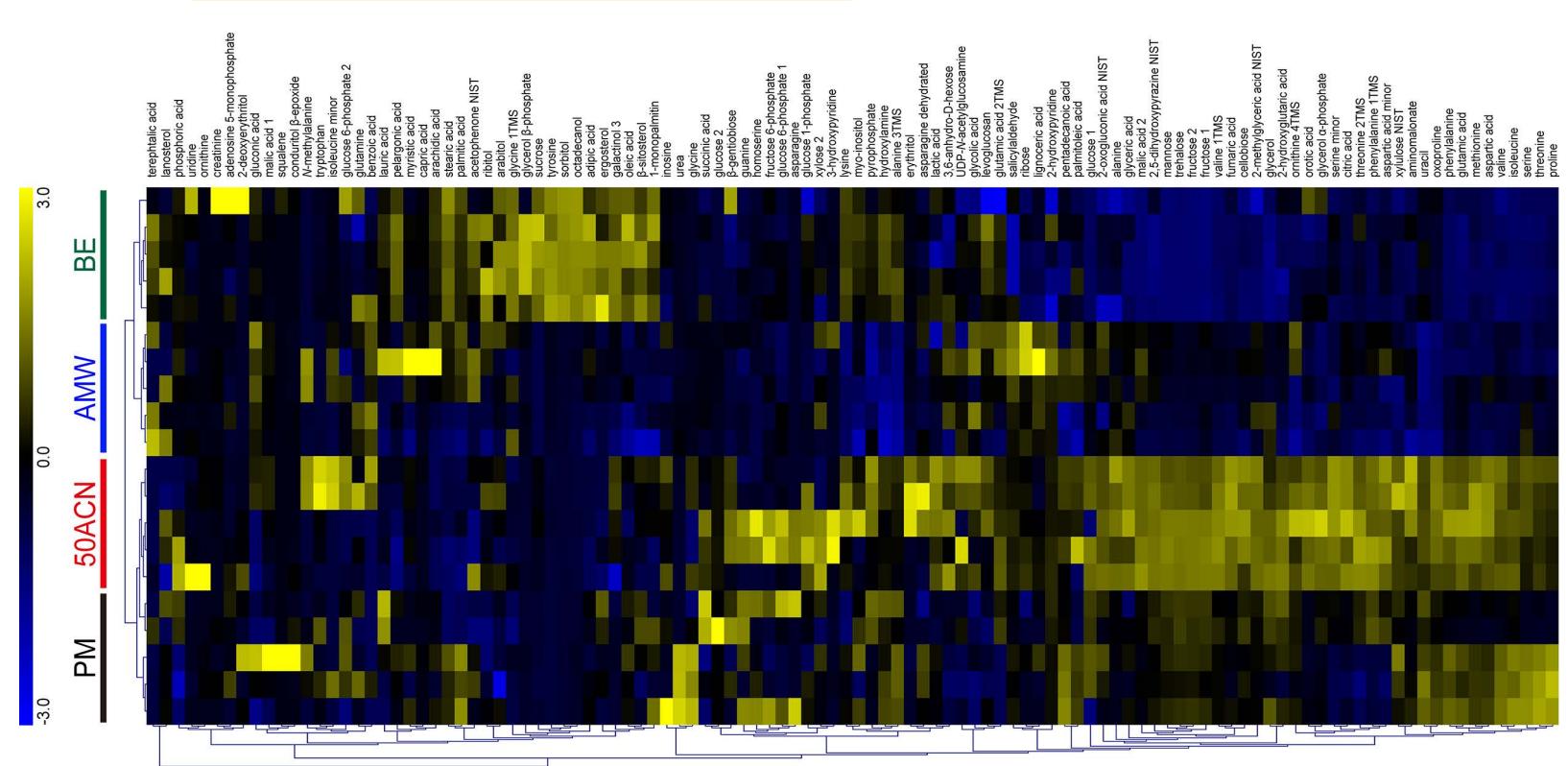


Evaluation and Optimization of Metabolome Sample Preparation Methods for *Saccharomyces cerevisiae*

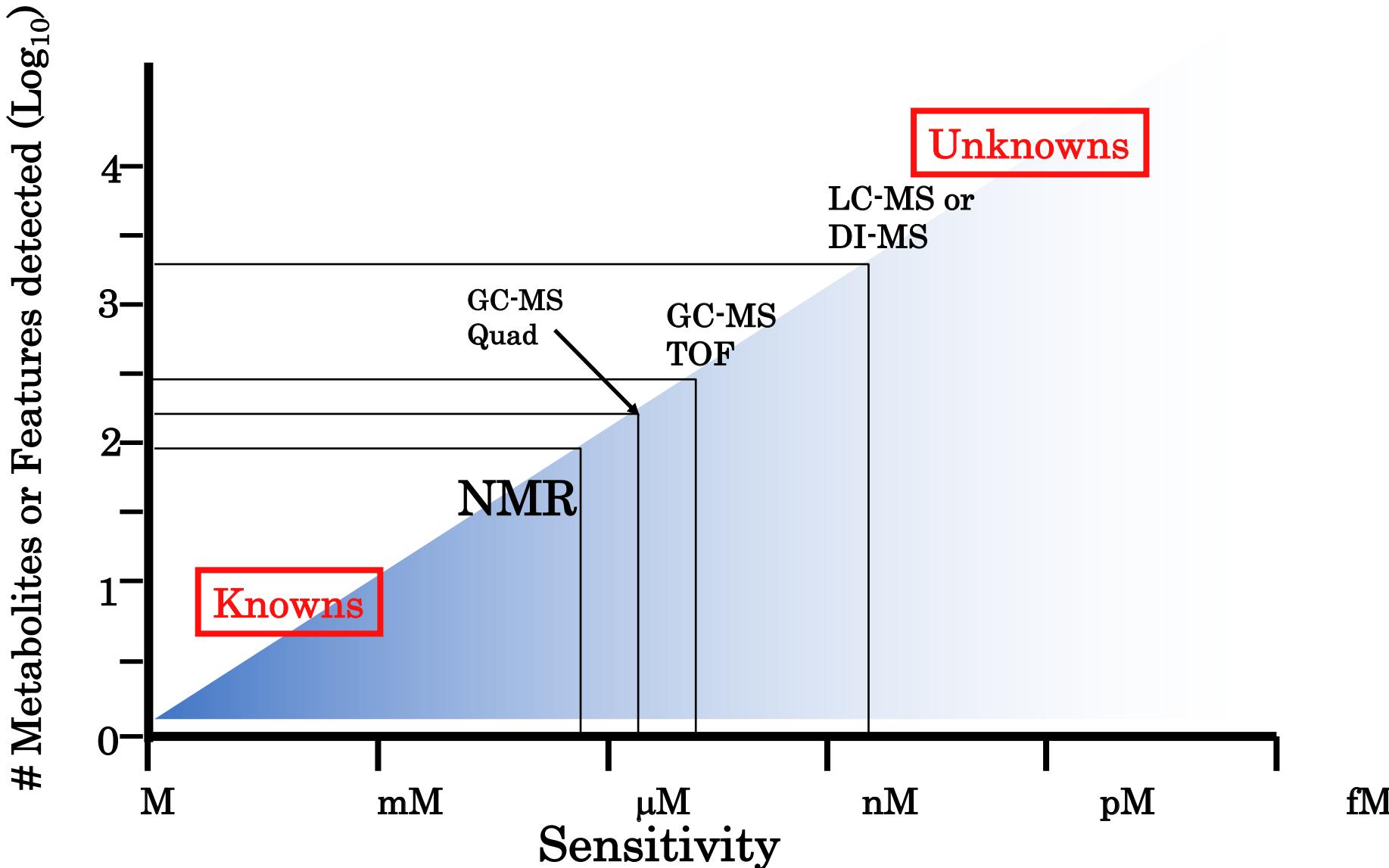
Sooah Kim,[†] Do Yup Lee,[‡] Gert Wohlgemuth,[§] Hyong Seok Park,[†] Oliver Fiehn,[§]
and Kyoung Heon Kim^{*,†}



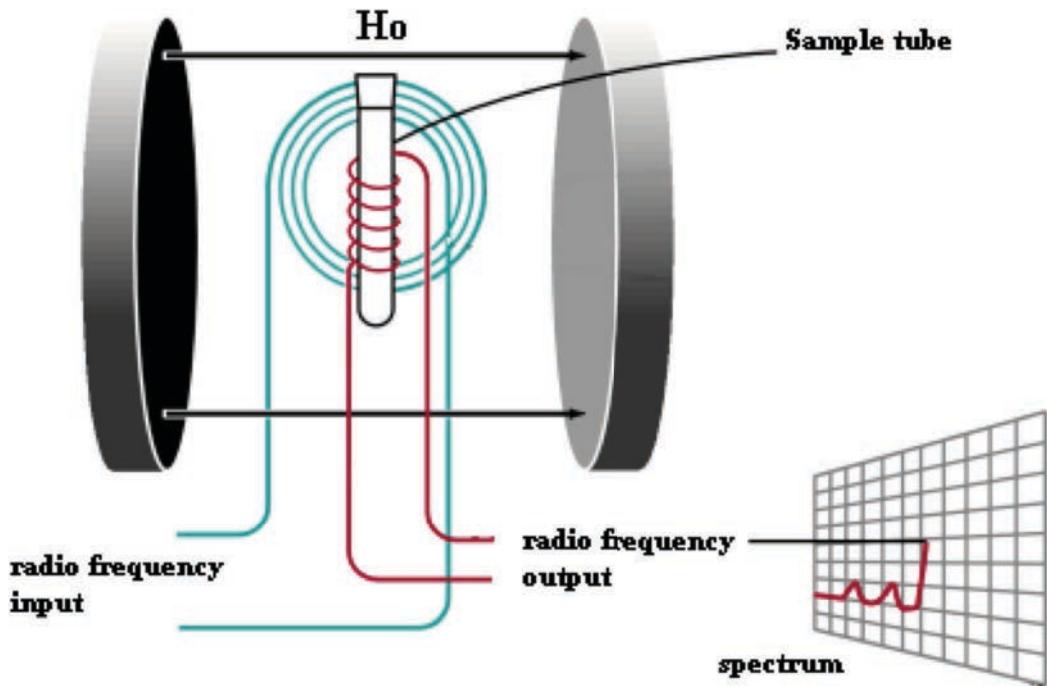
PM = Pure Methanol
50ACN = 50% Acetonitrile
AMW = Acetonitrile/methanol/ water
Boiling Ethanol

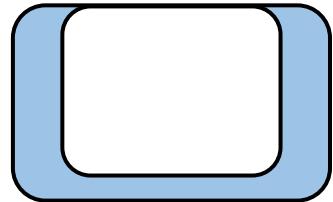


Technology & Sensitivity

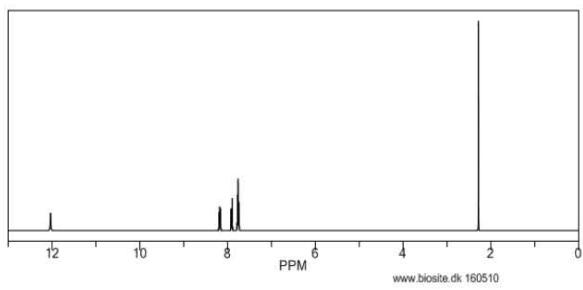


Nuclear magmatic resonance (NMR)

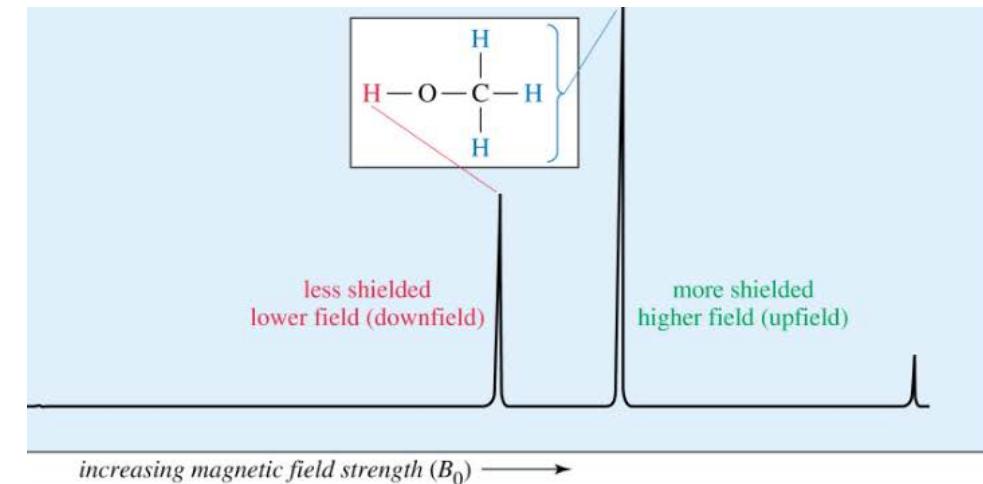




Apply energy
(Radio frequency)

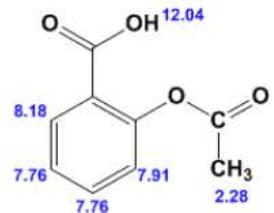


Strong magnetic field



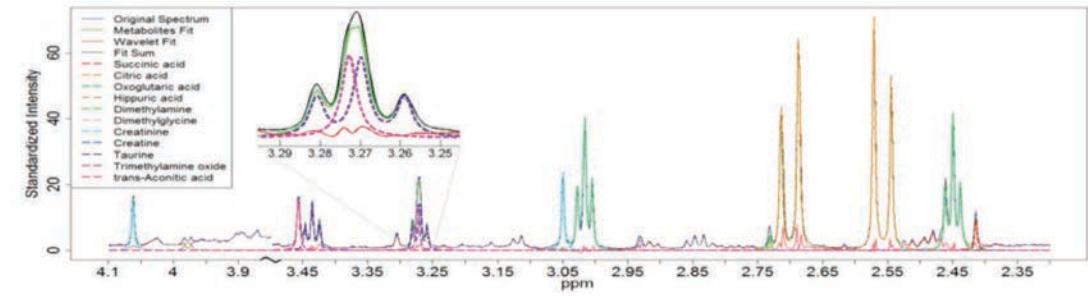
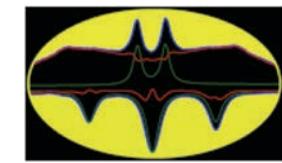
NMR spectrum

↓ Interpret



Structure

rNMR



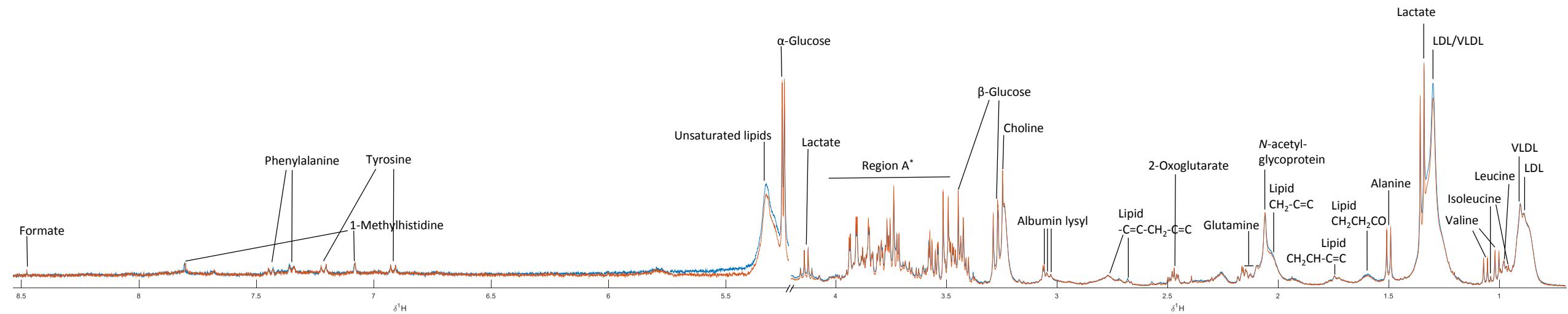
Dr. Sakchai Hongtong

<https://orgspectroscopyint.blogspot.com/2013/07/spectroscopy-data-of-aspirin.html>

<http://rnmr.nmrfam.wisc.edu>

<http://batman.r-forge.r-project.org>

Serum and Plasma CPMG NMR Spectra



Analyst: Jutarop Phetcharaburanin (21/05/2018)

Spectrometer: Bruker Ascend 400 MHz (128 scans)

Sample: Fasting serum (blue) and plasma (red)

Spectra: CPMG spin-echo

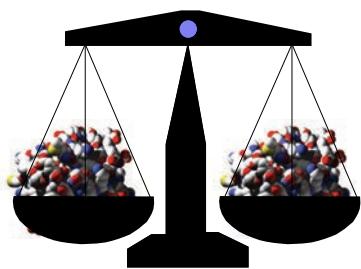
Metabolite assignment:

- Imperial College London's in-house database
- Chenomx Profiler
- STOCSY
- Nicholson *et al.* (1995), Anal Chem.
- Phetcharaburanin *et al.* (2016), J Proteome Res.

*Region A contains signals from glycerol, glucose and amino acid CH protons.

To identify these signals, 2-D NMR and spike-in of standard chemical experiments are required.

Mass spectrometry (MS)



John B. Fenn

“Mass spectrometry is the art of measuring atoms and molecules to determine their molecular weight. Such mass or weight information sometime sufficient, frequently necessary and always useful in determining the identity of a species...”

Nobel prize winner 2002



1. Hyphenated techniques

- GC-MS
- LC-MS
- CE-MS

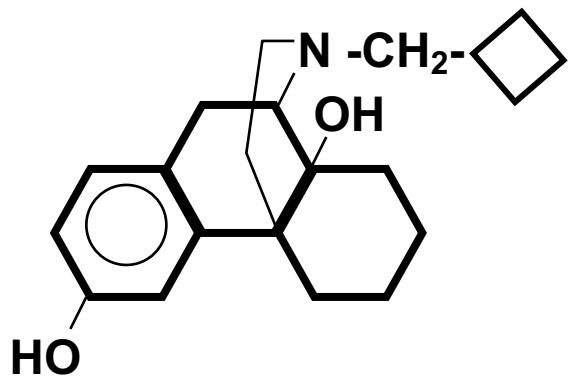
2. Direction injection mass spectrometry



MS Principles

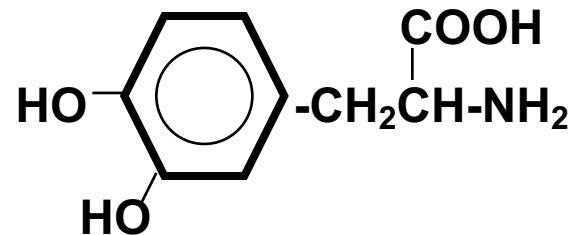
- Different compounds can be uniquely identified by their mass

Butorphanol



MW = 327.1

L-dopa



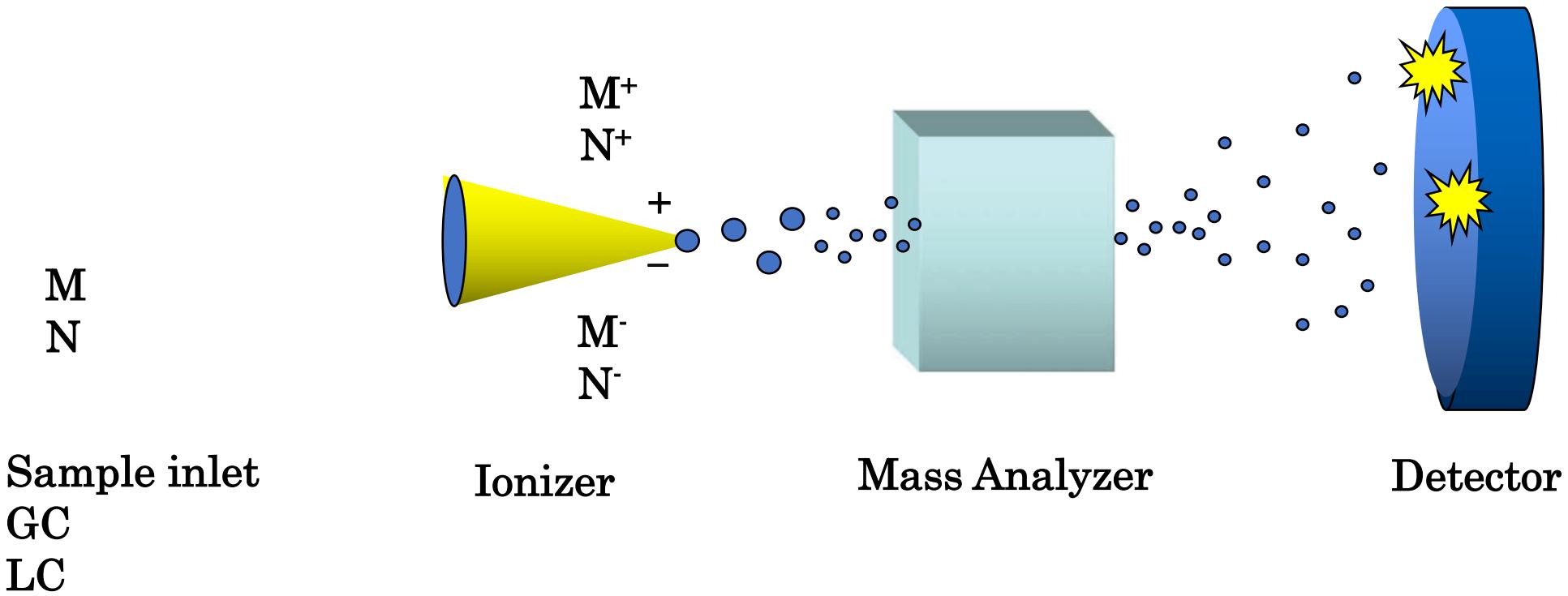
MW = 197.2

Ethanol

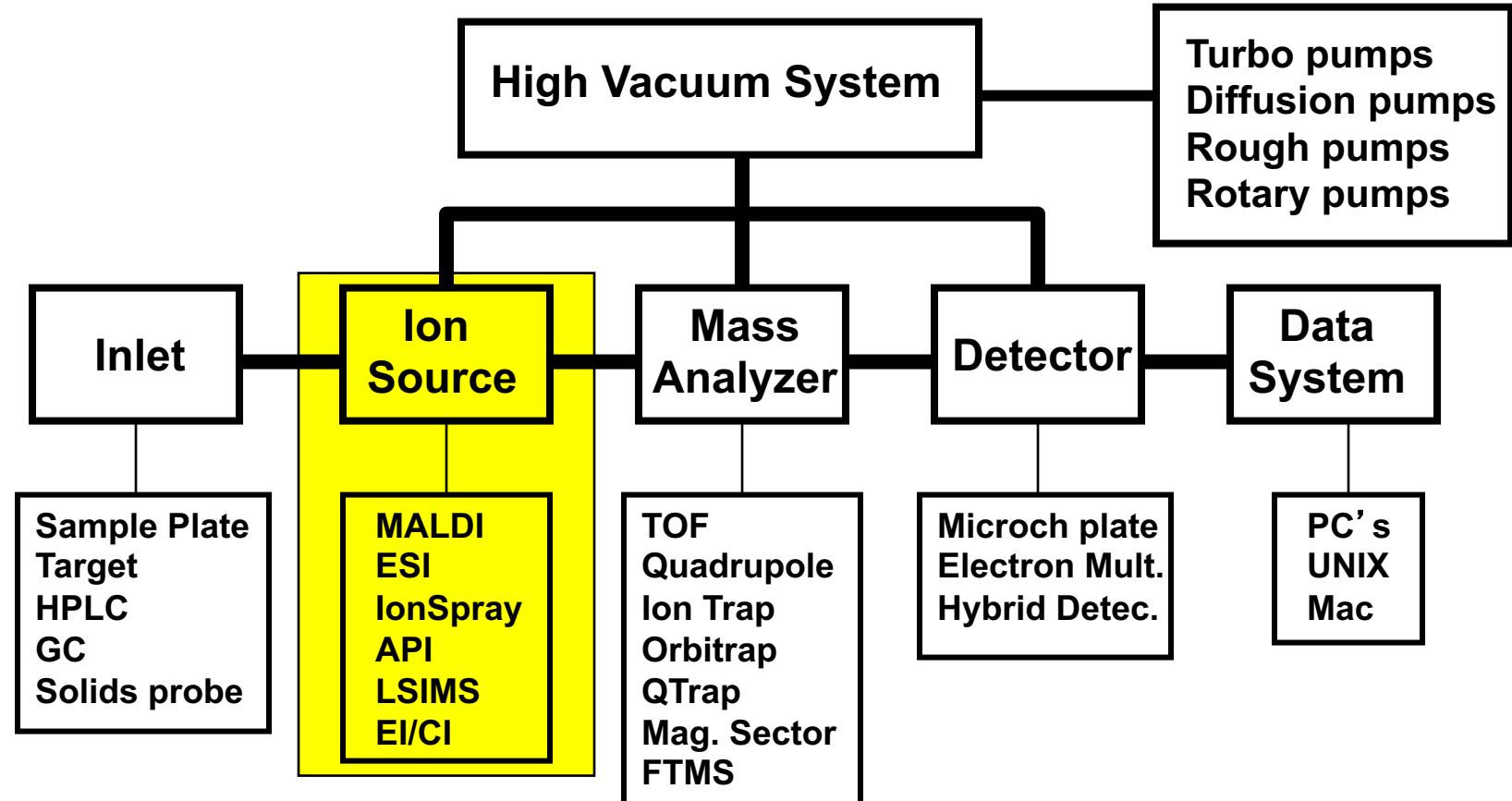
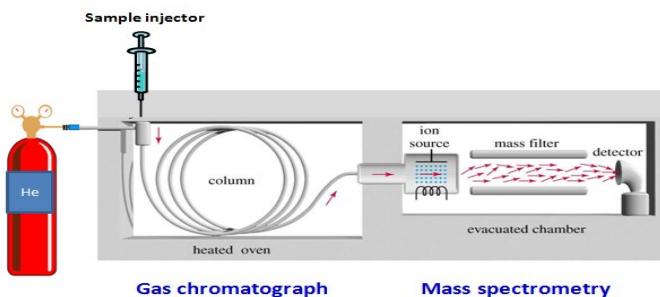


MW = 46.1

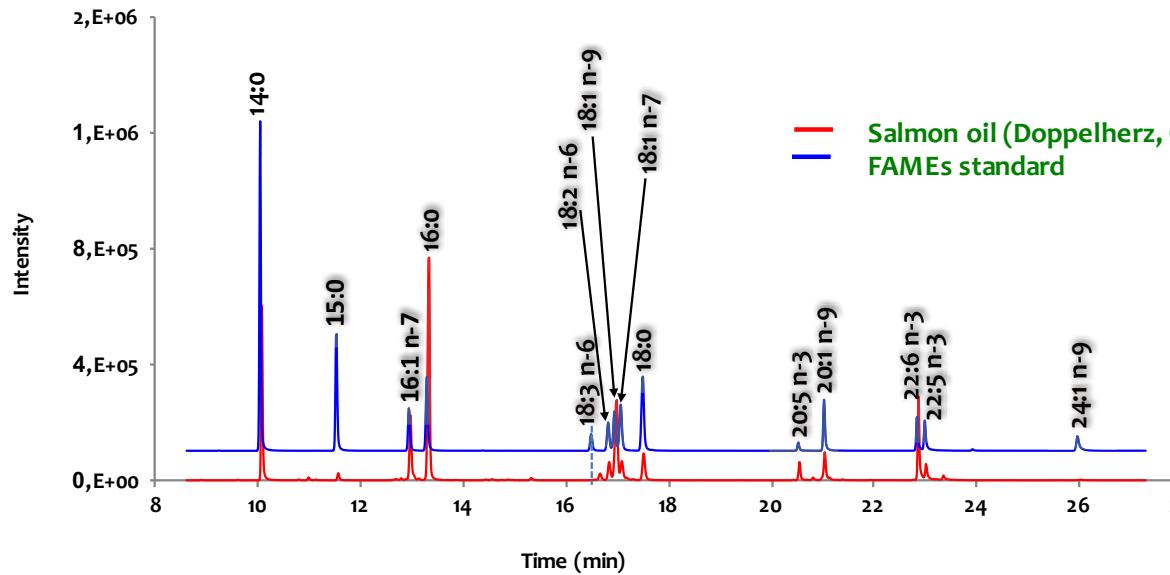
Mass Spec Principles



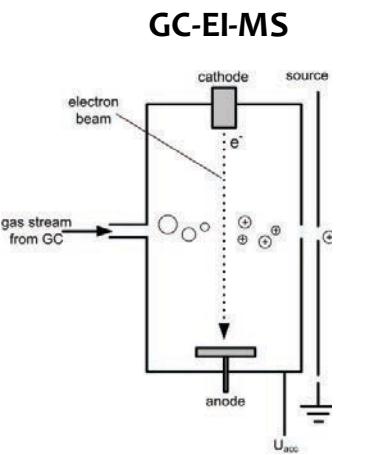
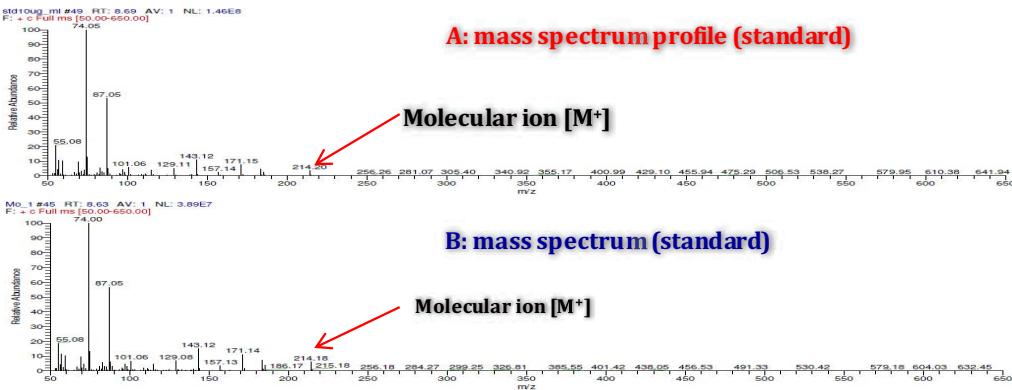
Mass Spectrometer Schematic



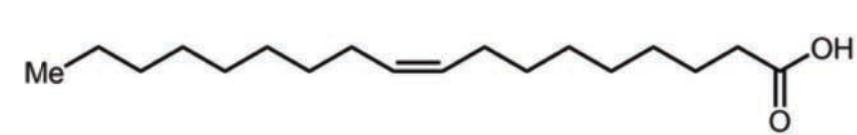
Output



A: mass spectrum profile (standard)

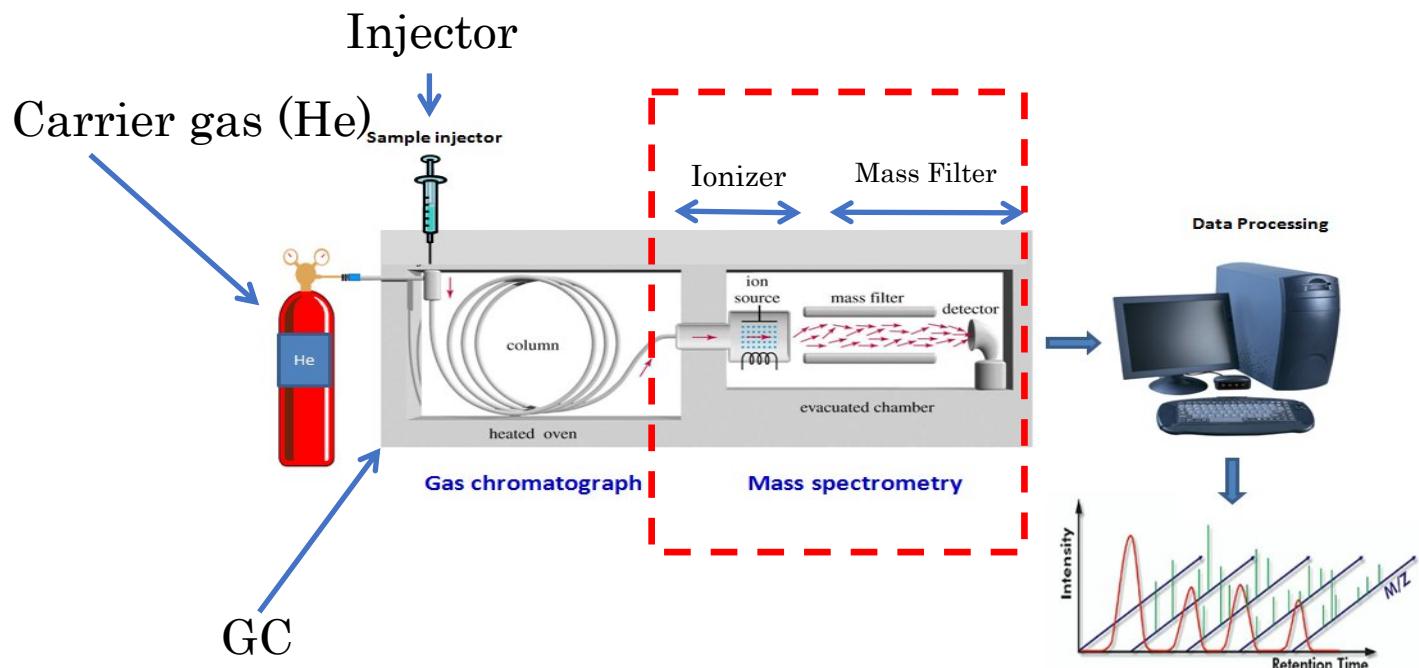


EI = Electron ionization

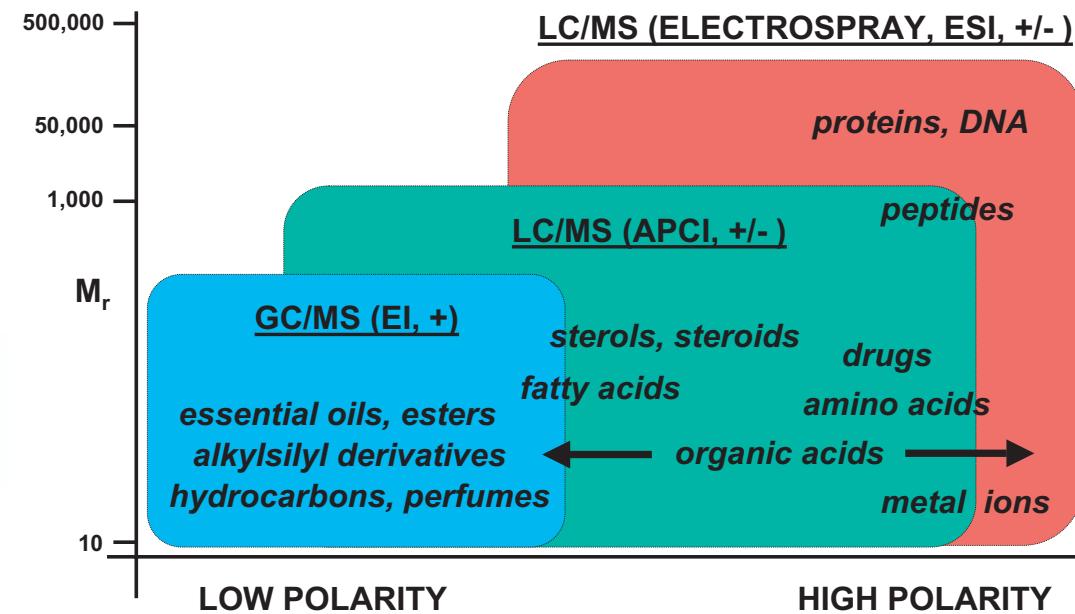


Oleic acid (18:1 n=9)

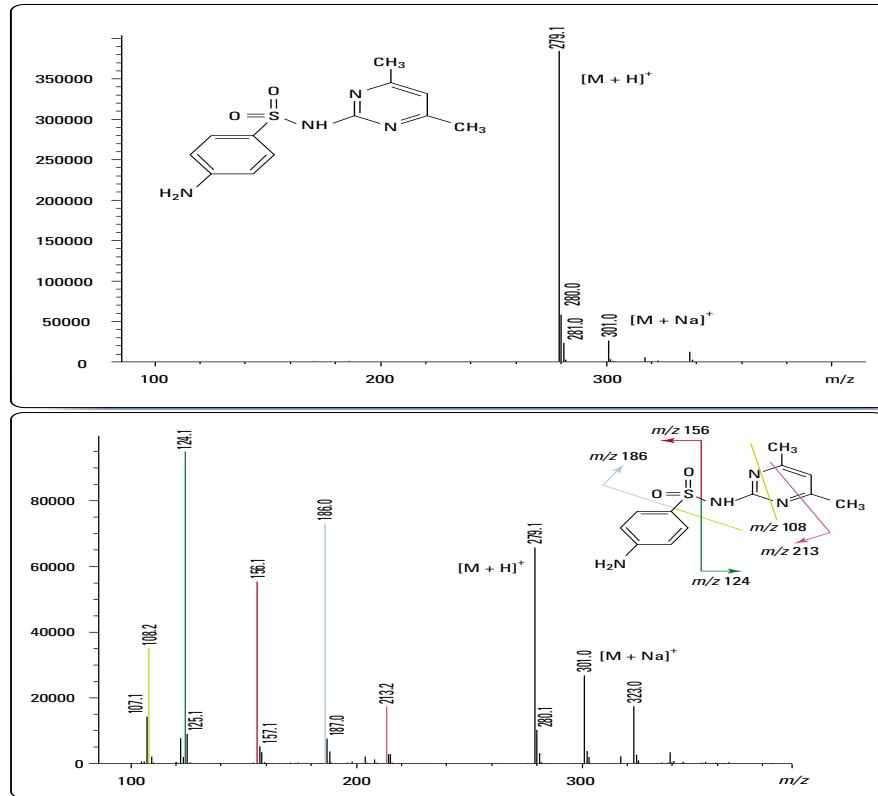
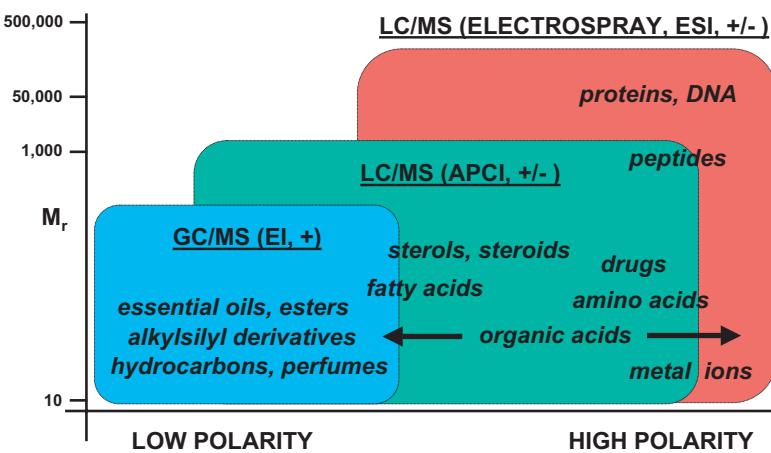
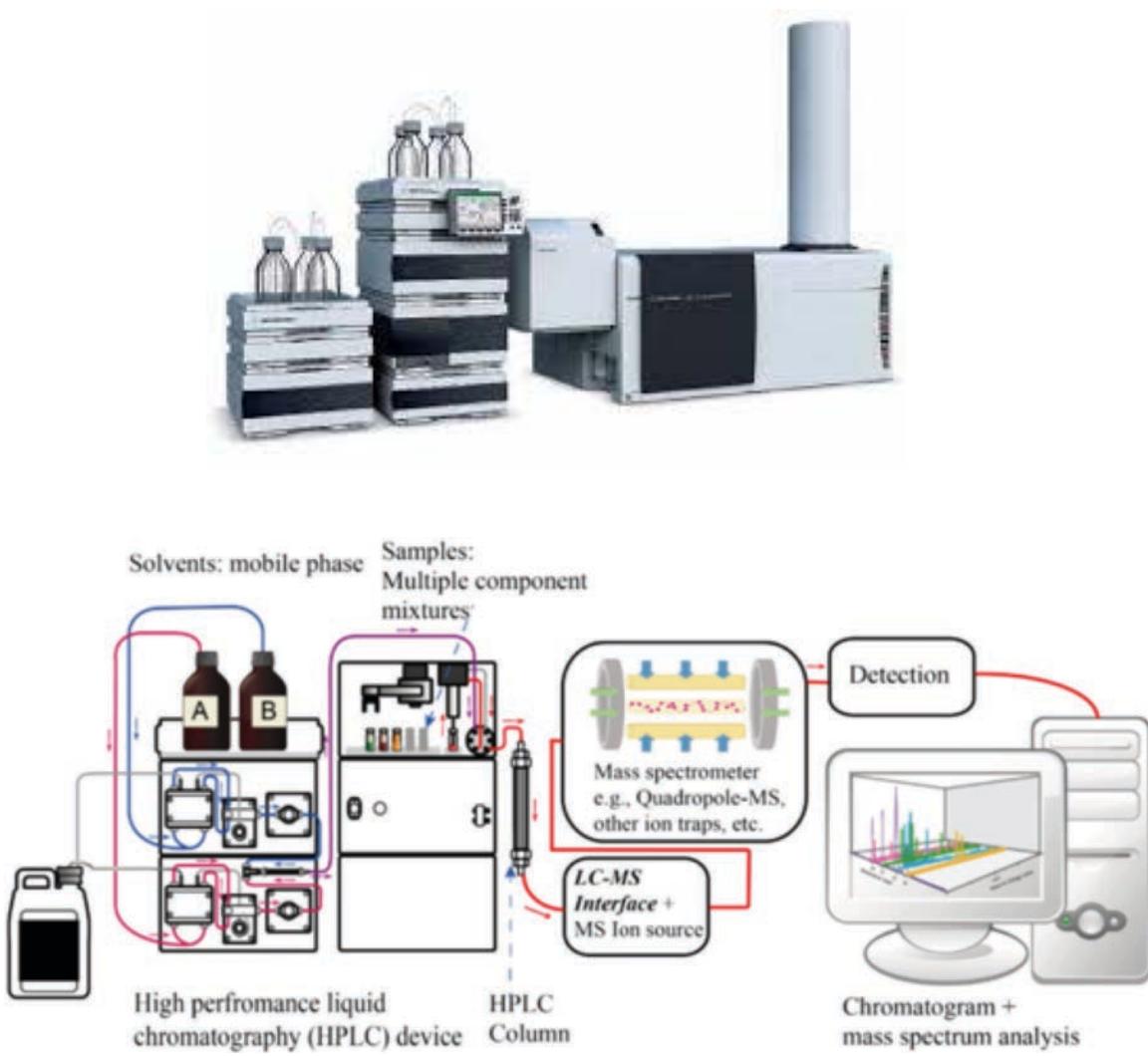
GC-MS



1. Mobile phase: He and H₂
2. GC: Column: polar, mid-polar and non-polar
3. Ionizer: Electron ionization (EI), Chemical Ionization (CI)
4. Mass analyzer: Quadrupole (S and T), TOF or Q-TOF



Liquid Chromatography MS (LC-MS)



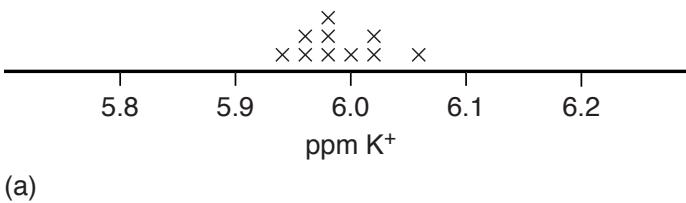
Language in Analytical Chemistry

Accuracy and precision

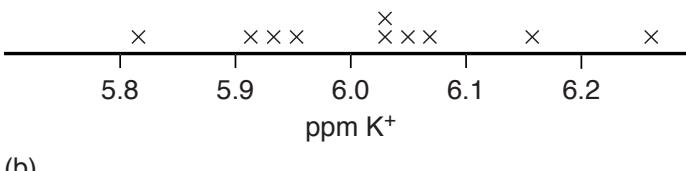
Accuracy: % Error = (Obtained result – expected result)/expected X 100

- Standard reference material (National Institute of Standard and Technology)
 - Spiking experiment

Precision: A measure of variability = SD/mean X 100 (%RSD)

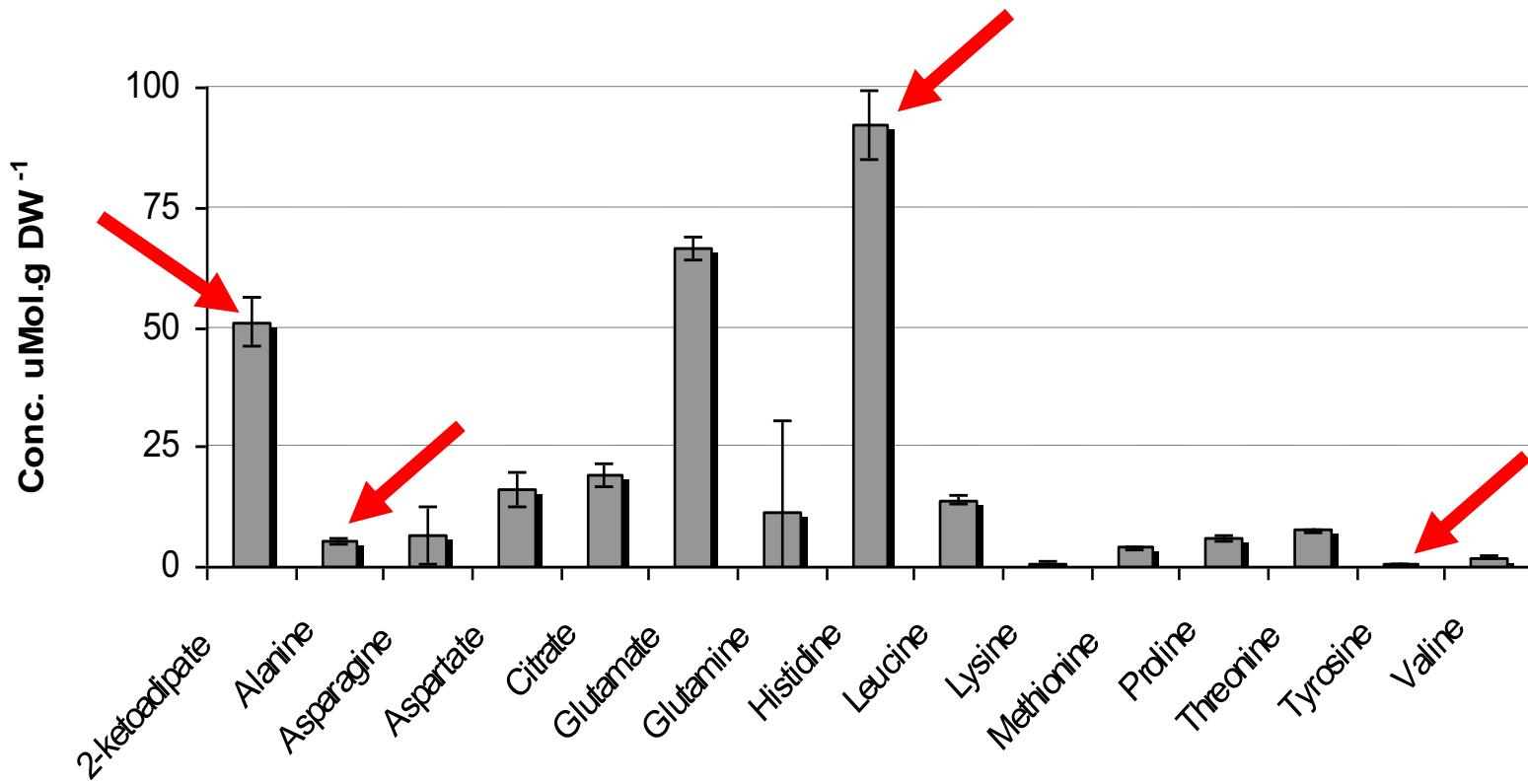


(a)



(b)

Good Reproducibility (precision)



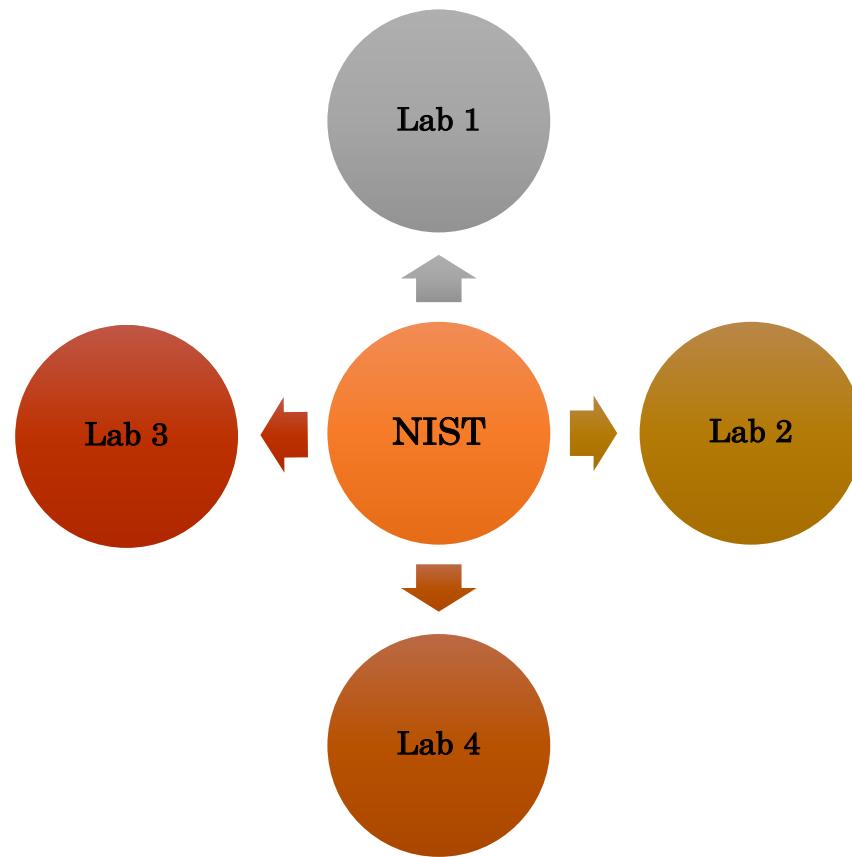
% Relative standard deviation (%RSD)

$$\% \text{RSD} = (\text{SD}/\text{mean}) \times 100$$

How can we measure “accuracy”



1. Standard Reference Material (SRM)

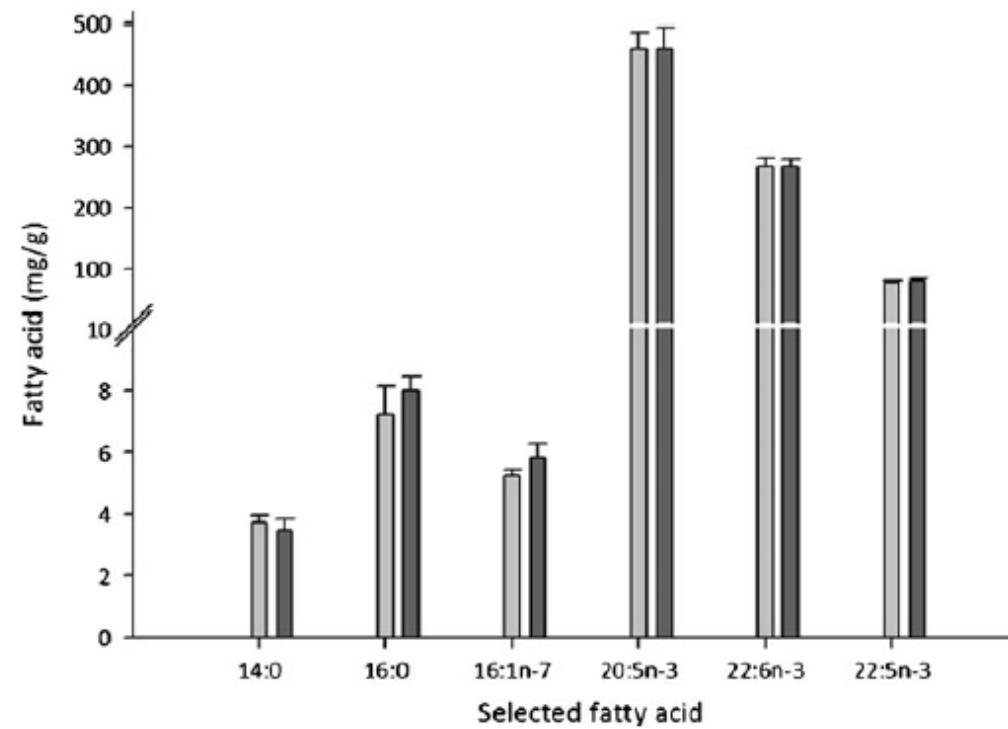


SRM



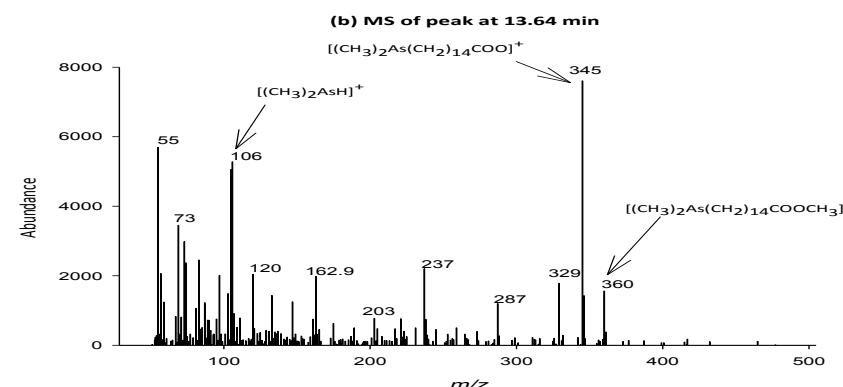
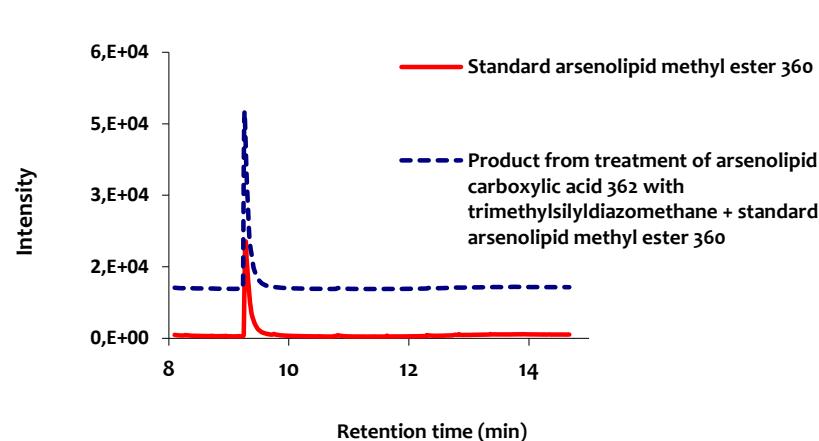
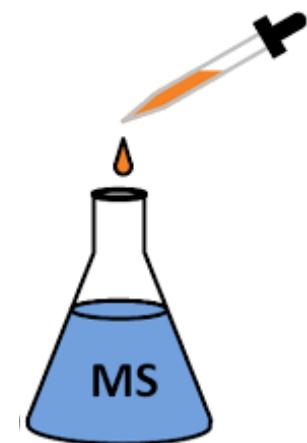
In-house SRM

Experimental value (microwave method)
Certified value



2. Spiking experiment

- % Recovery
- Identity of metabolites



Exp. Conc. ($\mu\text{g As g}^{-1}$)	Measured Conc. ($\mu\text{g As g}^{-1}$)	% Conversion
0.20	0.22 ± 0.02	109 ± 8
0.60	0.66 ± 0.01	110 ± 2
1.11	1.11 ± 0.16	98 ± 14

1. <http://unipub.uni-graz.at/obvugrhs/download/pdf/215808?originalFilename=true>

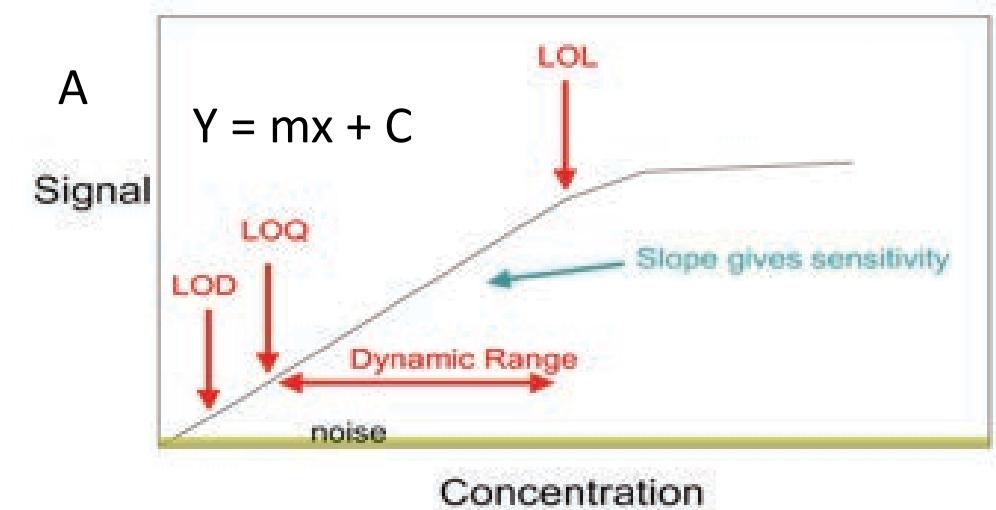
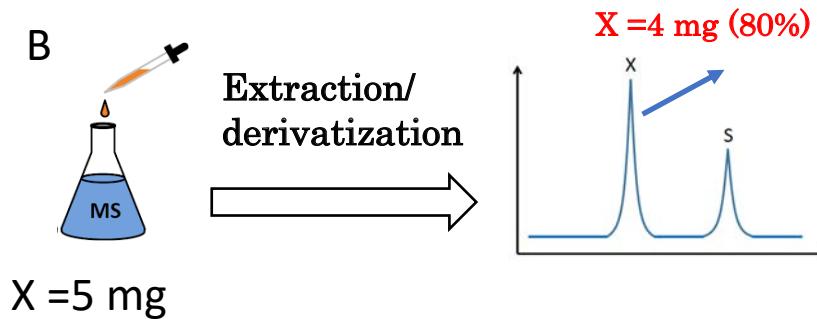
1. Quantitative analysis in metabolomics

- Semi quantification (relative)
- Absolute quantification

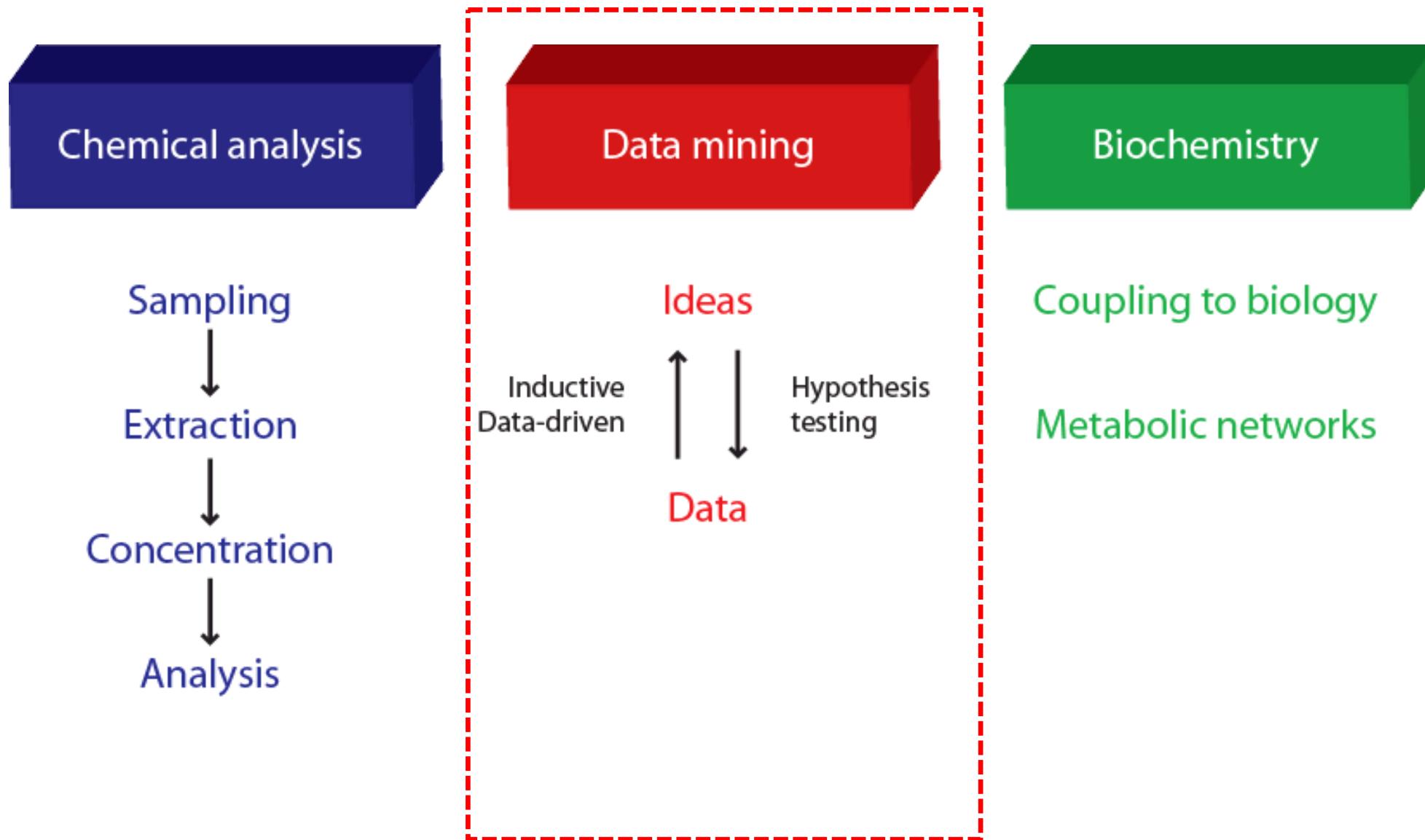
2. Internal standard

3. External standard

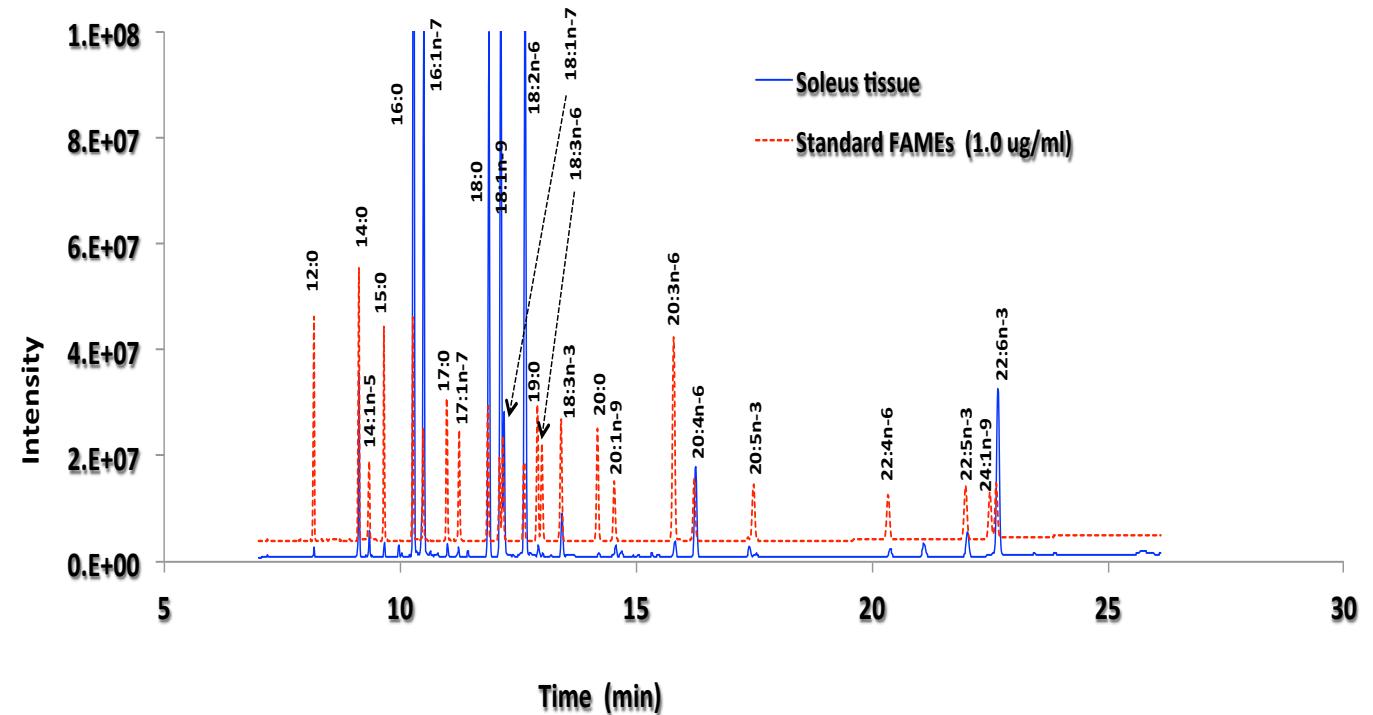
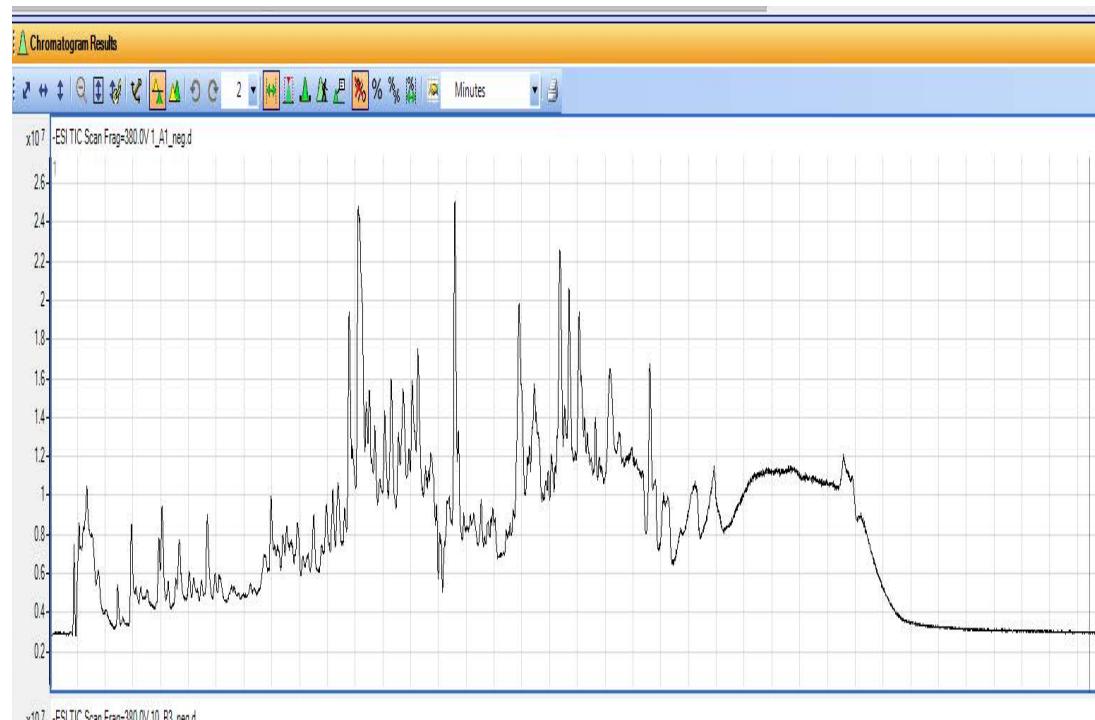
4. Standard addition

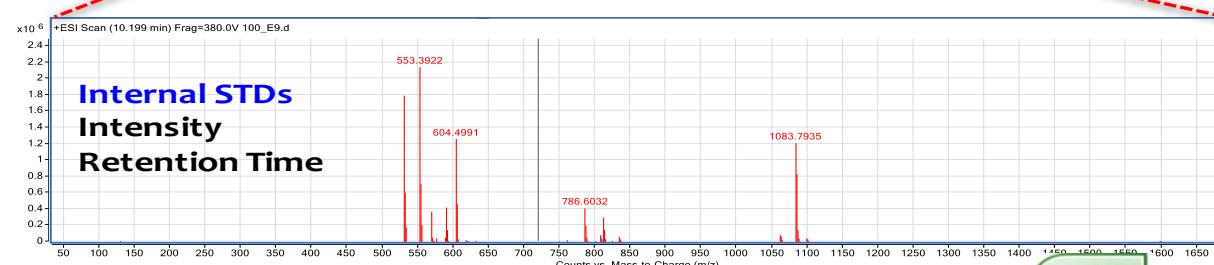
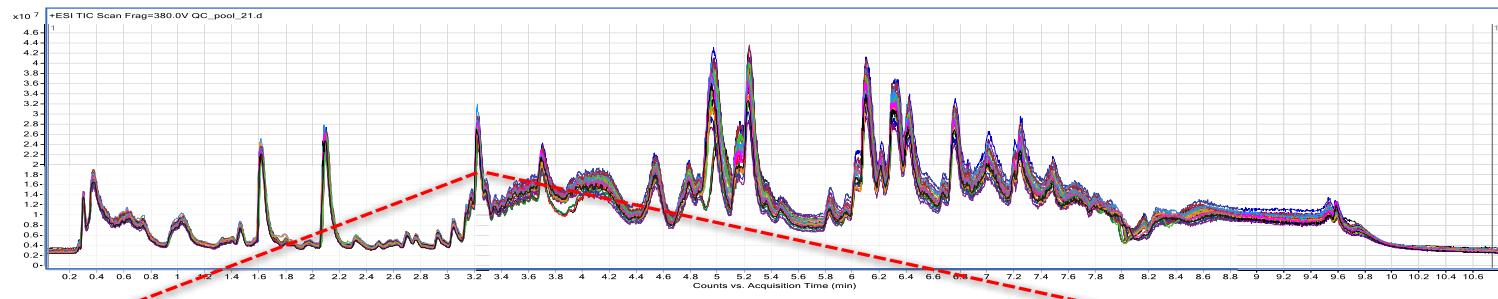


Metabolomics workflow



Data processing (?) and analysis (?)



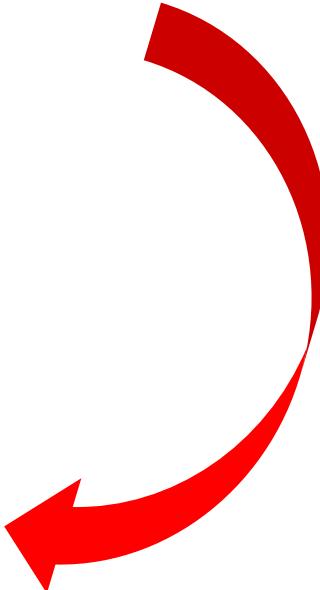


- Internal standards (Area and RT)
- Unknown peaks (Feature: Area and RT)

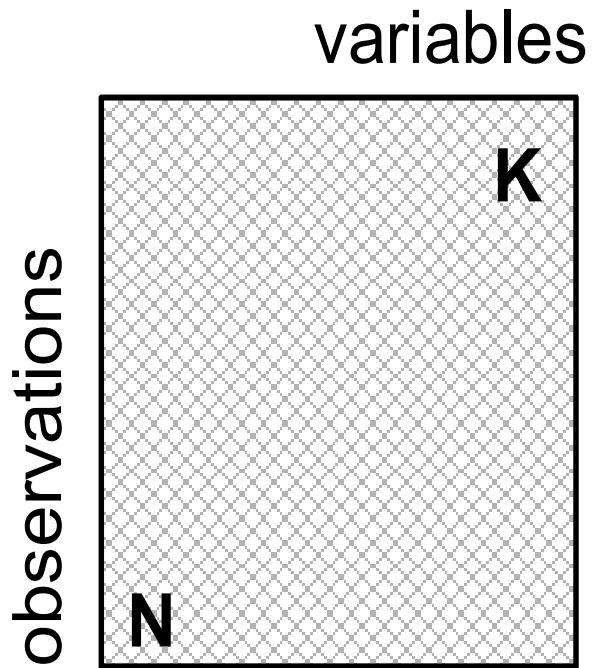


1600 unidentified metabolites (x 2)

Compound	Blank	Con1	Con_2	Con_3	Con_4	H56_5	TreatM_1	TreaM_2	TreamM_3
785.9907@8.700584		1	747011	2,16E+07	3220174	1738801	2821005	5205011	1888888 2,01E+07
187.0633@2.0974243		1	3,06E+07	3,16E+07	2,85E+07	3,15E+07	3,39E+07	3,46E+07	2,40E+07 2,85E+07
519.3327@6.1120315		16062	7,97E+07	7,43E+07	6,75E+07	6,57E+07	6,49E+07	5,82E+07	7,33E+07 5,57E+07
495.3281@6.316343		42381	7,38E+07	6,14E+07	6,04E+07	5,91E+07	6,05E+07	5,80E+07	6,13E+07 6,03E+07
521.348@6.404964		1	7,50E+07	7,22E+07	7,79E+07	8,05E+07	7,81E+07	6,67E+07	7,52E+07 5,85E+07
523.3635@6.7539687		101894	7,02E+07	6,20E+07	6,94E+07	6,60E+07	6,33E+07	5,66E+07	6,52E+07 5,35E+07



Metabolomics data structure



N Observations

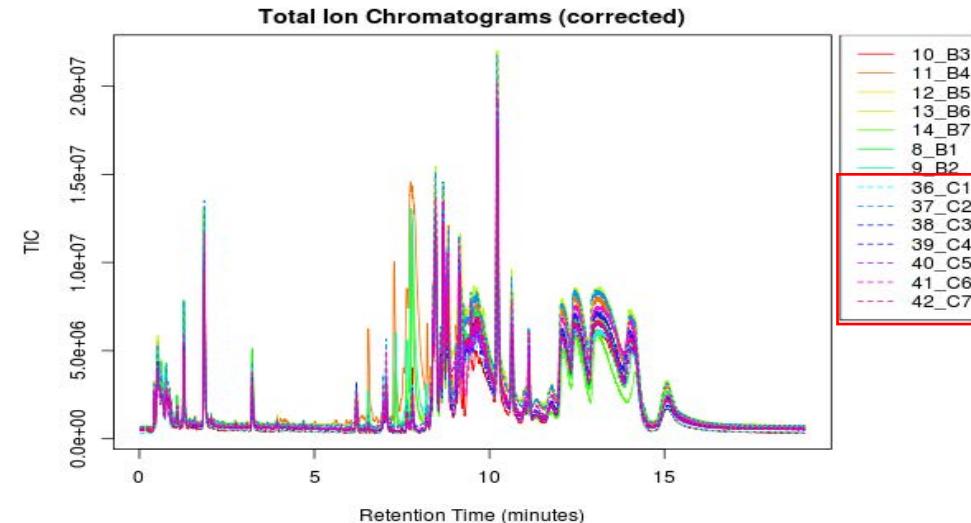
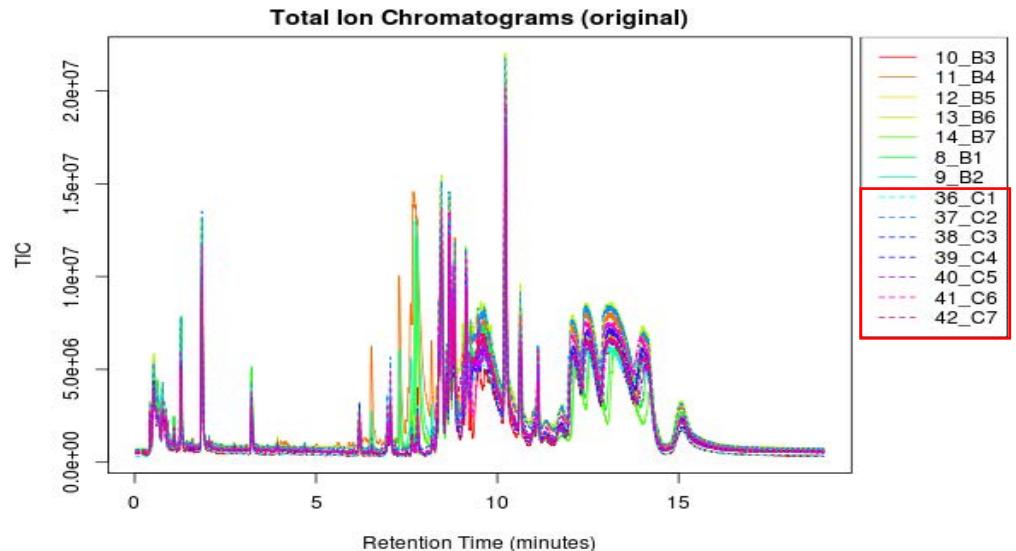
- Analytical samples
- Chemical compounds
- Process time points
- Chemical reactions
- Biological individuals
- Subject individuals

K Variables

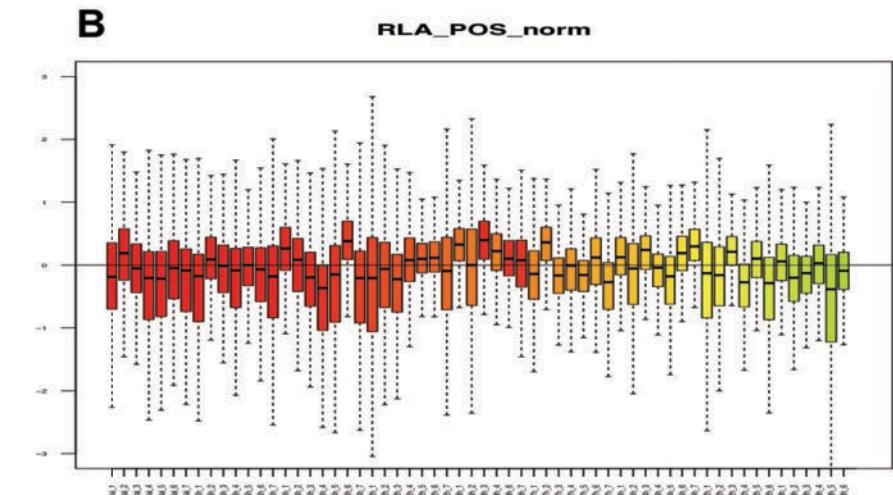
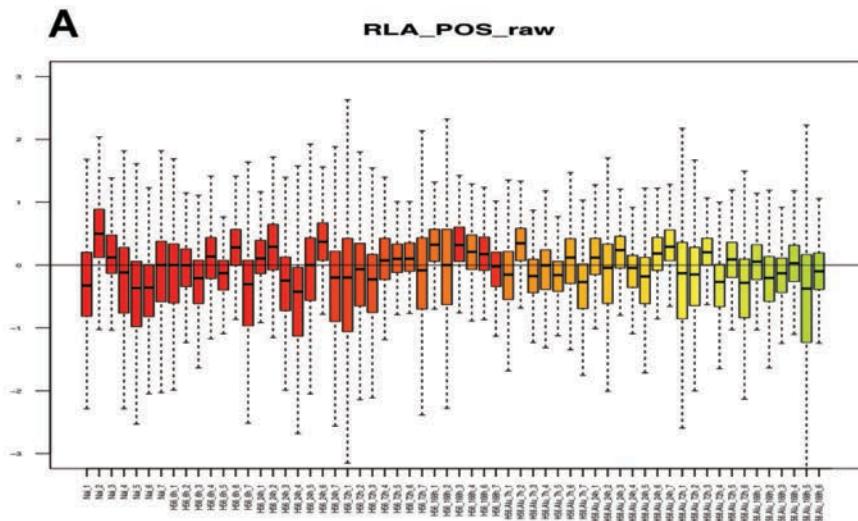
- From spectra
 - NMR, IR, UV, MS, ESCA, X-ray, ...
- From separation
 - HPLC, GC, TLC, Electrophoresis, Trace elements, ...

Data processing

Peak alignment



Normalization



Data scaling - VARIABLES

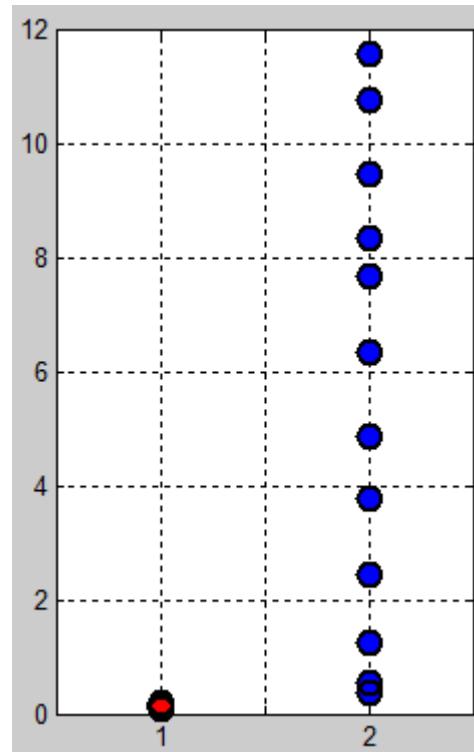
Examples: Center, UV-scaling, Pareto, quantile normalization,
Log 2 transformation

- Problem: Variables can have substantially different ranges
- Example: LOWARP - polymers characterized for strength and warp

Response		5 wrp1	6 wrp2	7 wrp3	8 wrp4	9 wrp5	10 wrp6	11 st1	12 st2	13 wrp7	14 st3	15 st4	16 wrp8	17 st5	18 st6
0.9	5.0	0.2	1.0	0.3	4.2	232	15120	1.2	2190	26390	1.3	2400	0.7		
3.7	7.3	0.7	1.8	2.5	5.4	150	12230	1.8	905	20270	2.1	1020	0.6		
3.6	6.9	0.9	2.1	4.8	9.4	243	15550	1.2	1740	21180	1.4	1640			
0.6	3.1	0.3	0.4	0.4	1.1	188	11080	1.0	1700	17630	1.0	1860	0.5		
0.3	2.1	0.3	0.3	0.8	1.1	172	11960	1.2	1810	21070	1.3	1970	0.5		
1.2	5.0				245	15600	1.1	2590	25310	1.3	2490	0.6			
2.3	3.9	0.3	0.4	0.7	1.4	242	13900	1.5	1890	21370	1.6	1780			
2.6	5.9	0.4	0.2	0.7	1.2	243	17290	1.6	2130	30530	1.6	2320	0.7		
2.2	5.3	0.2	0.7	0.6	2.0	204	11170	1.0	1670	19070	1.1	1890	0.6		
5.8	7.0	0.9	1.0	5.6	11.8	262	20160	1.6	1930	29830	1.8	1890			
0.8	2.9	0.5	0.6	1.1	2.0	225	14140	1.3	2140	22850	1.3	2110	0.7		
2.8	5.1	1.0	1.2	2.7	6.1	184	15170	1.9	1230	23400	2.1	1250	0.6		
1.1	4.7	0.6	0.9	1.3	3.5	198	13420	1.4	1750	23790	1.4	1930	0.7		
1.9	4.7	1.0	1.0	2.8	5.4	234	16970	1.5	1920	25010	1.6	1790	0.7		
2.9	5.9	0.5	0.6	1.0	6.6	239	15480	1.5	1800	23140	1.6	1730			
5.5	7.9	0.8	2.4	5.5	9.3	256	18870	1.5	1880	28440	1.8	1790			
3.2	6.0	0.3	0.5	1.5	5.2	249	16310	1.5	1860	24710	1.7	1780			

Data for 2 variables

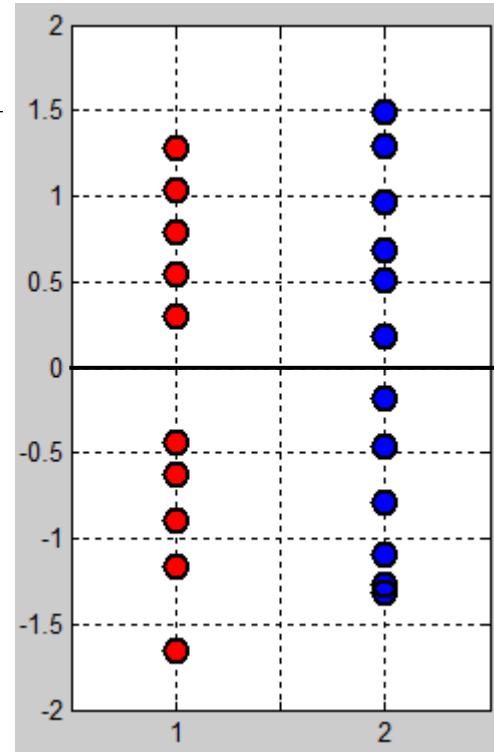
v1	v2
0.2	0.38
0.21	0.54
0.19	1.23
0.17	2.45
0.18	3.76
0.21	4.87
0.11	6.34
0.14	7.65
0.132	8.32
0.121	9.45
0.14	10.76
0.09	11.55



Unscaled - v1 is not easily visualized together with v2

UV-scaling
Subtract avg
Divide by stdev

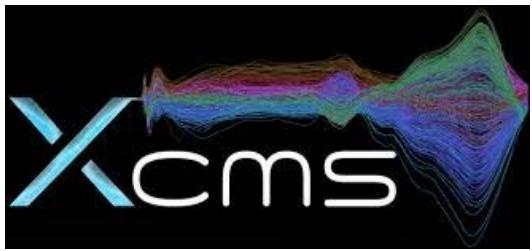
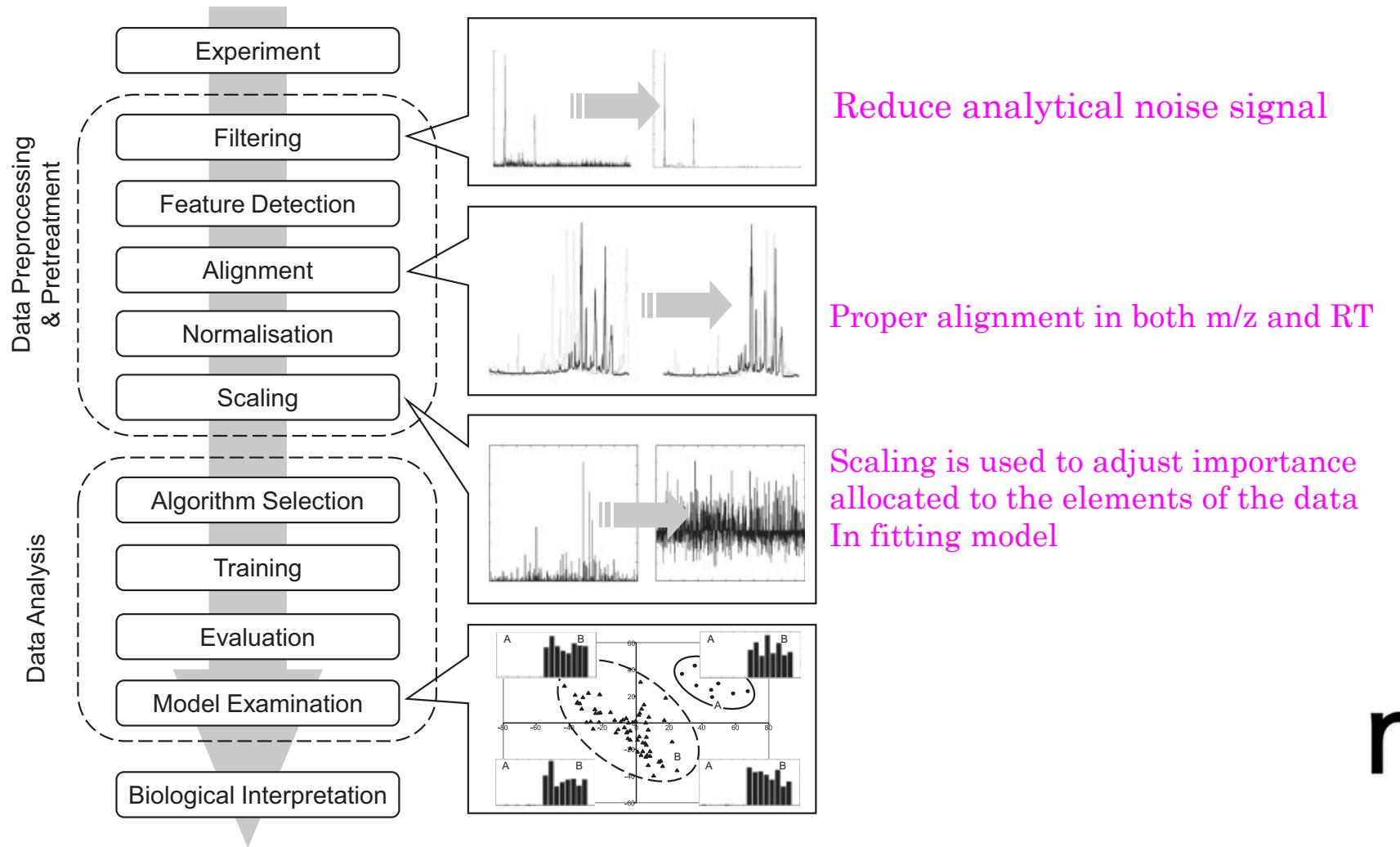
v1 UV	v2 UV
-0.27	-1.34
-0.32	-1.26
-0.27	-1.09
-0.34	-0.78
-0.26	-0.46
-0.27	-0.18
-0.31	0.19
-0.32	0.51
-0.26	0.68
-0.26	0.96
-0.27	1.29
3.17	1.49



Scaled – both variables are more easily understood

1. Automated

2. Unautomated



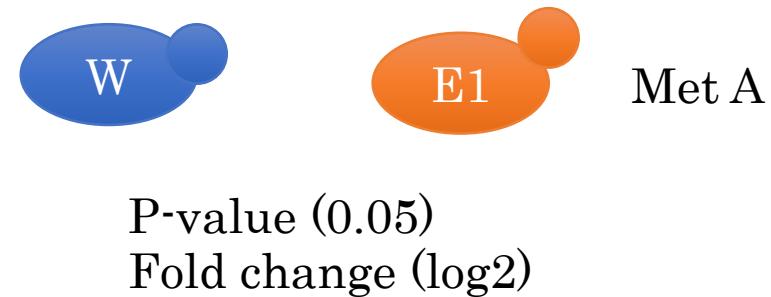
metabox M_x

Data Analysis

1. Univariate analysis
2. Multivariate analysis

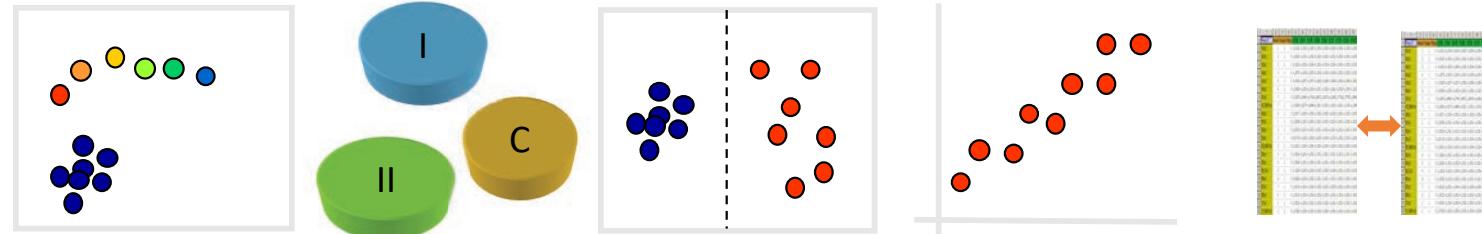
Univariate Analysis

- Univariate means a single variable
- If you measure a population using some single measure such as height, weight, test score, IQ, a metabolite



Multivariate analysis

“Multivariate statistics is a form of statistics encompassing the simultaneous observation and analysis of more than one outcome variable. **The application of multivariate statistics is multivariate analysis”**



Overview	Classification	Discrimination	Regression	Multi-block
Trends Outliers Quality Control Biological Diversity Patient Monitoring	Pattern Recognition Diagnostics Healthy/Diseased Toxicity mechanisms Disease progression	Discriminating between groups Biomarker candidates Comparing studies or instrumentation	Prediction methods Biomarker candidates Multivariate calibration QSAR modeling	Understanding and comparing multiple blocks of omics data Metab vs Proteomic vs Genomic
PCA	SIMCA	PLS-DA OPLS-DA	PLS & OPLS	O2PLS & OnPLS

Other MVA methods

- Multivariate Curve Resolution
- N-way methods (PARAFAC family)

Univariate or Multivariate in metabolomics ??

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**Trials and tribulations of 'omics data analysis:
assessing quality of SIMCA-based multivariate models
using examples from pulmonary medicine**

sa M. Wheelock^{*ab} and Craig E. Wheelock^{*bc}



sa M. Wheelock



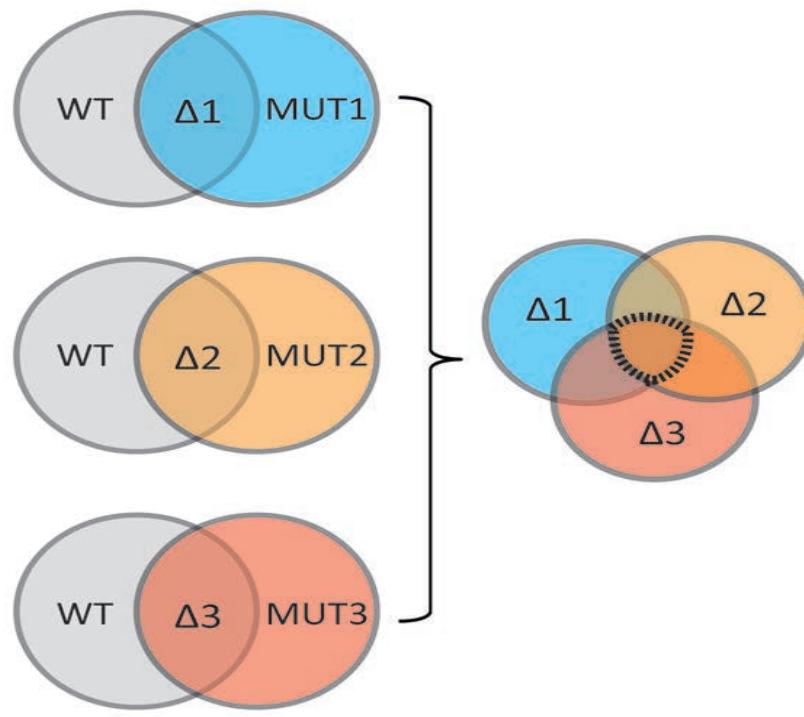
Craig E. Wheelock

Statistical challenges in the analysis of 'omics datasets

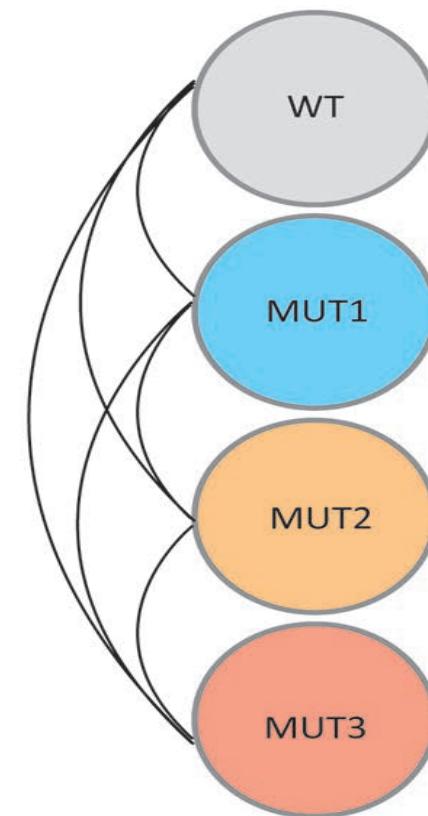
The discrepancies between the number of variables analyzed (*e.g.*, mRNA, proteins, metabolites) and the number of study subjects constitutes a major statistical challenge in large-scale omics investigations. These short-and-wide dataset structures are not conducive to traditional univariate statistical methods (*e.g.*, *t*-test), because the repeated hypothesis testing results in a high numbers of potential false positives. The most common way to correct for these high false positive rates is to apply some form of *p*-value correction, such as the False Discovery Rate (FDR) described by Benjamini Hochberg,¹² the *q*-value described by Storey,¹³ or Bonferroni correction.^{14,15} While the benefits of a reduction of false positives have made these methods the standard in the field for *e.g.*, transcriptomics,¹⁶ the downsides in terms of loss of statistical power to detect true positives are rarely discussed.^{17–20} In a previous

Strategy in untargeted analysis

Meta-analysis of independent two-group comparisons



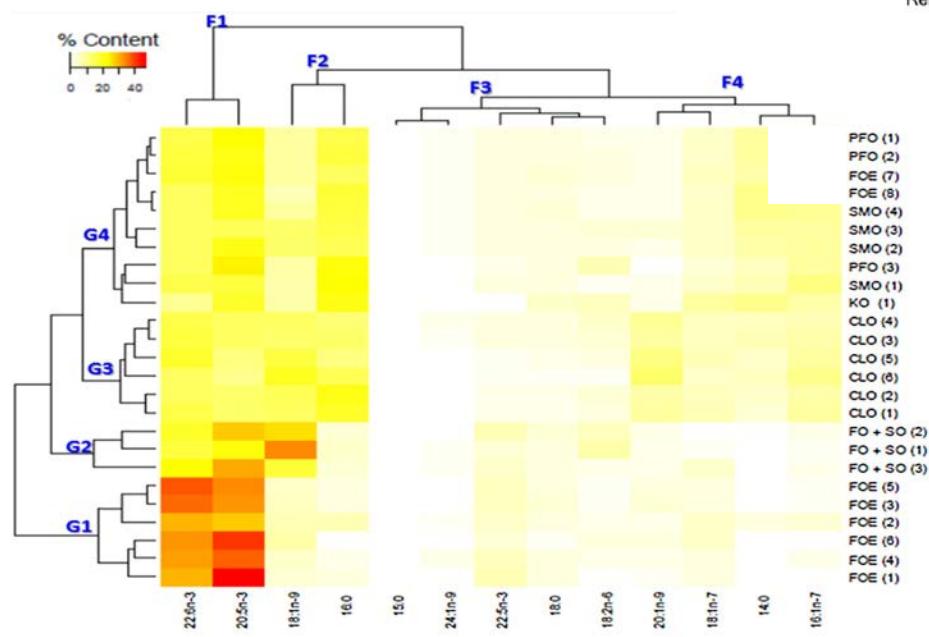
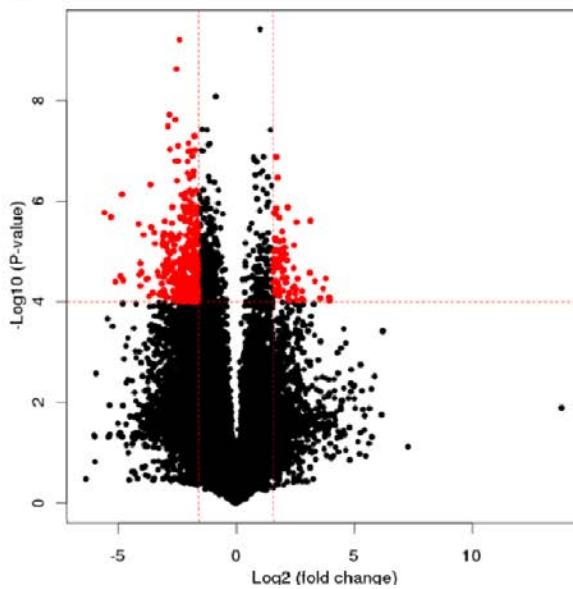
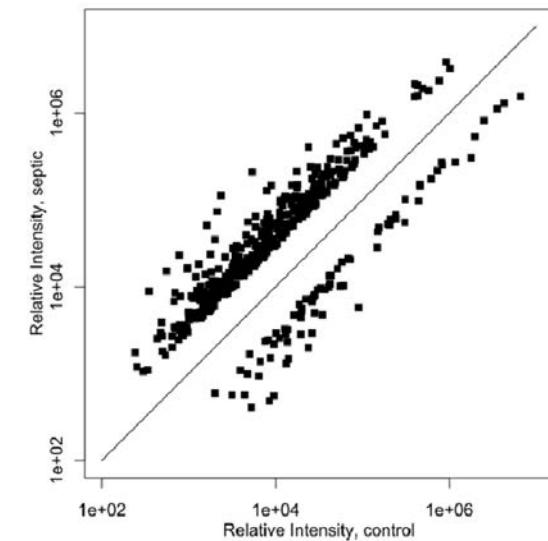
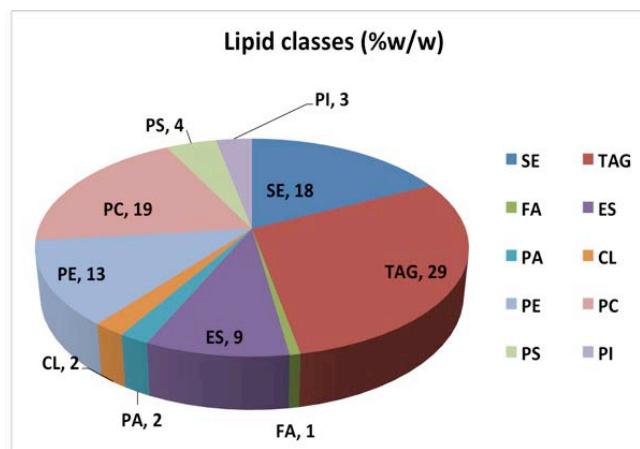
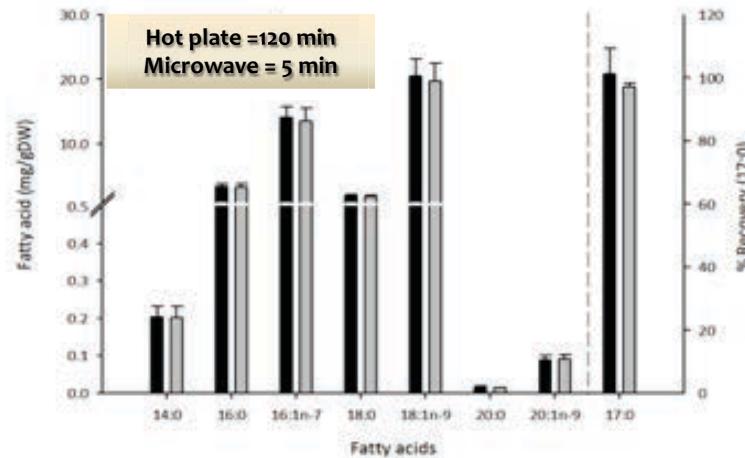
Multigroup analysis



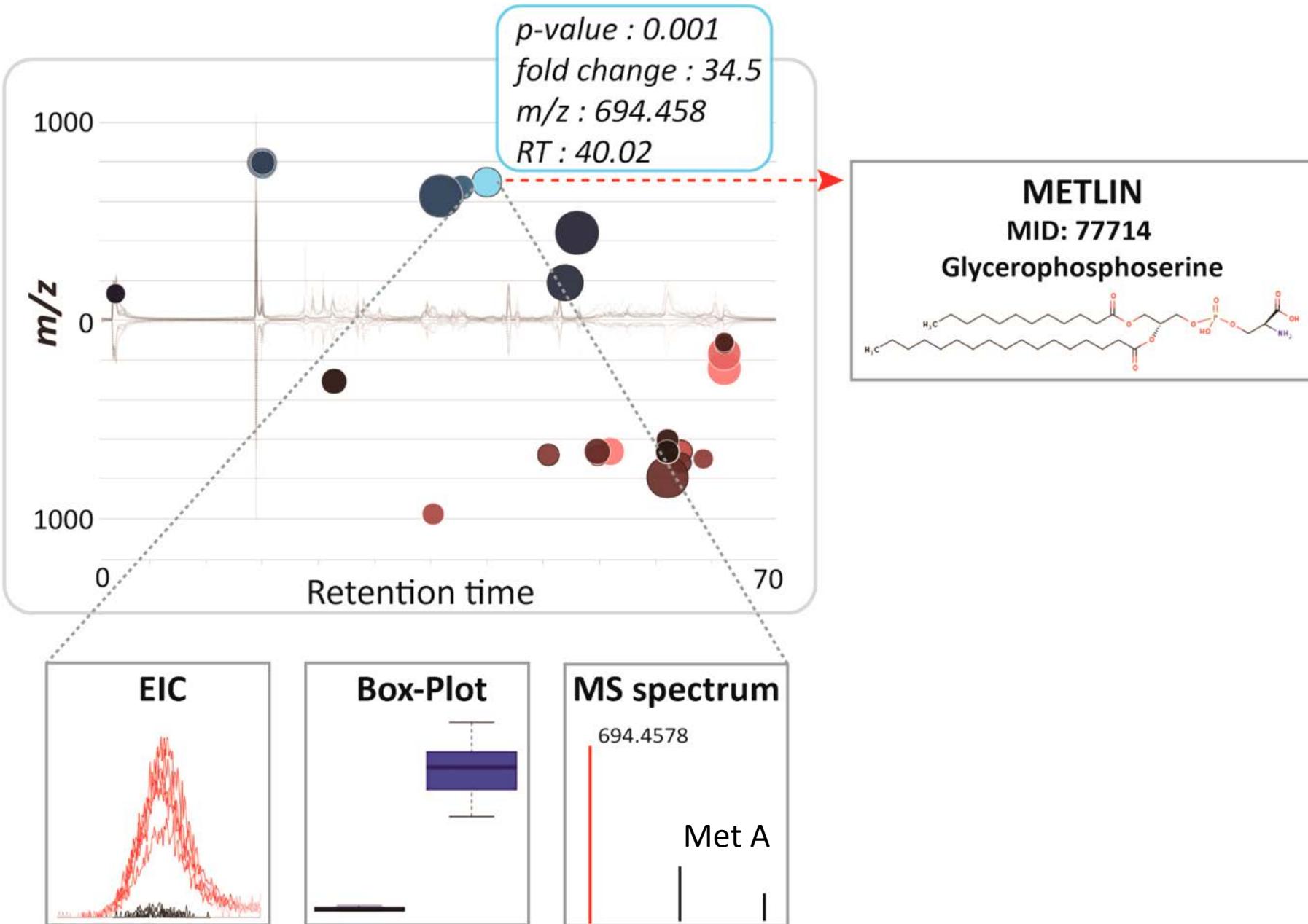
Two-group comparison

- Unpaired (independent) → different subjects (place and vaccine)
- Paired (dependent) → same subject (before and after)

Interpret metabolomics results ?



Cloud plot

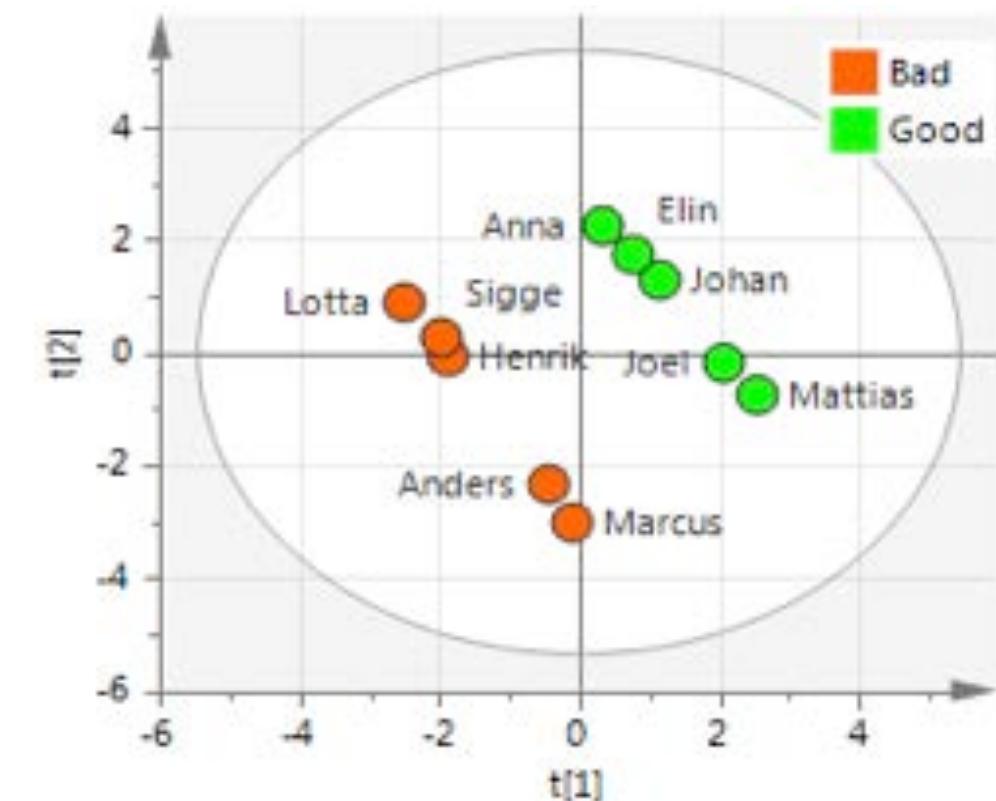


Principal Component Analysis (PCA)

ID / Labels / info					Hours of study/play			Physical variables			??	
Nr	Name	Surname	Grades	Size	Maths	Chem	Football	Height	Shoe nr	Hand length	Surname letters	Grades
1	Johan	Frisk	Good	Short	95	84	12	174	40	20.5	5	18.2
2	Mattias	Lundin	Good	Tall	92	97	23	191	44	23	6	18
3	Anna	Lundell	Good	Short	86	92	21	170	38	18.8	7	16.9
4	Joel	Nordlund	Good	Tall	91	87	9	189	43	22	8	17
5	Elin	Johansson	Good	Short	90	90	16	172	41	19	9	18.5
6	Henrik	Ekman	Bad	Short	49	39	120	168	40	20	5	12.6
7	Anders	Holler	Bad	Tall	38	45	112	188	44	22.5	6	12
8	Sigge	Hedlund	Bad	Short	45	35	98	173	39	19	7	10.4
9	Marcus	Magnuson	Bad	Tall	40	36	105	193	46	23.2	8	10.1
10	Lotta	Lundstrom	Bad	Short	35	41	99	170	38	18	9	11.8

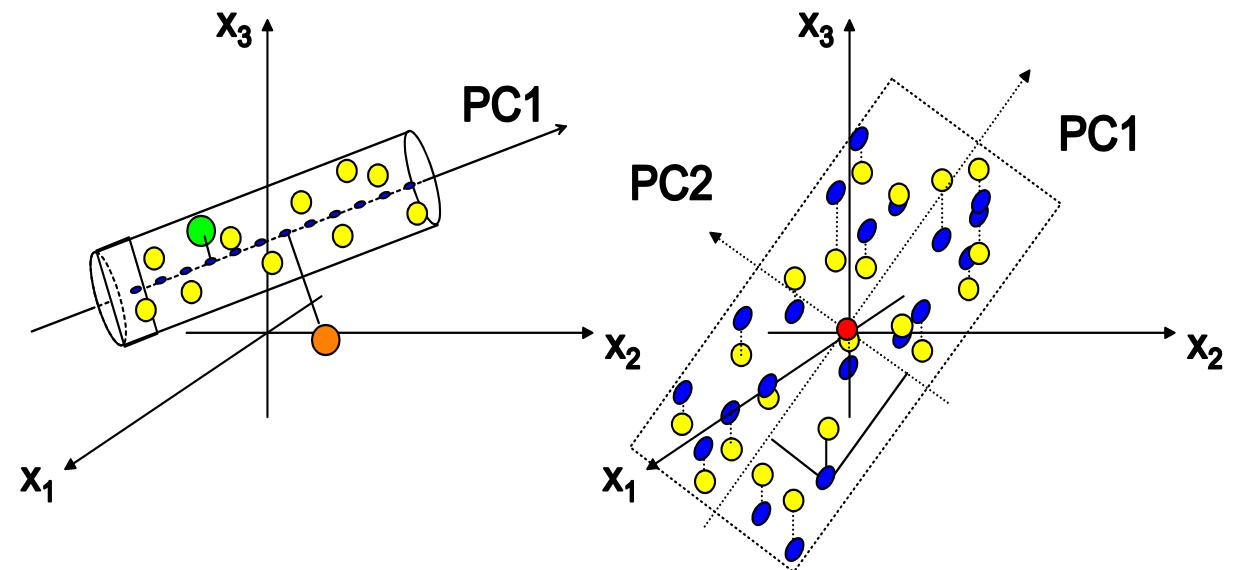
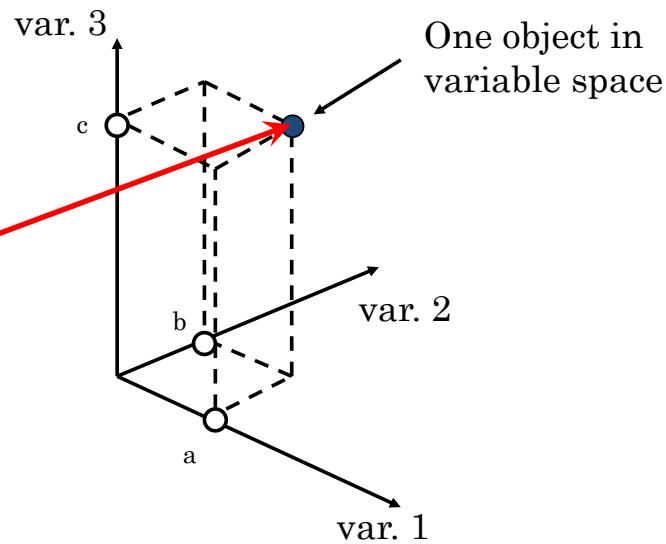
X

y



How does PCA work ?

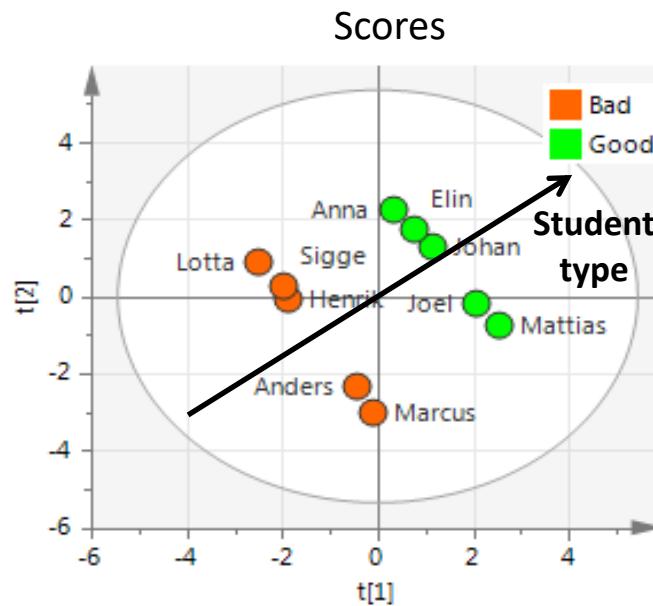
	Var 1	Var 2	Var 3
1			
2			
3	a	b	c
4			
...			
N			



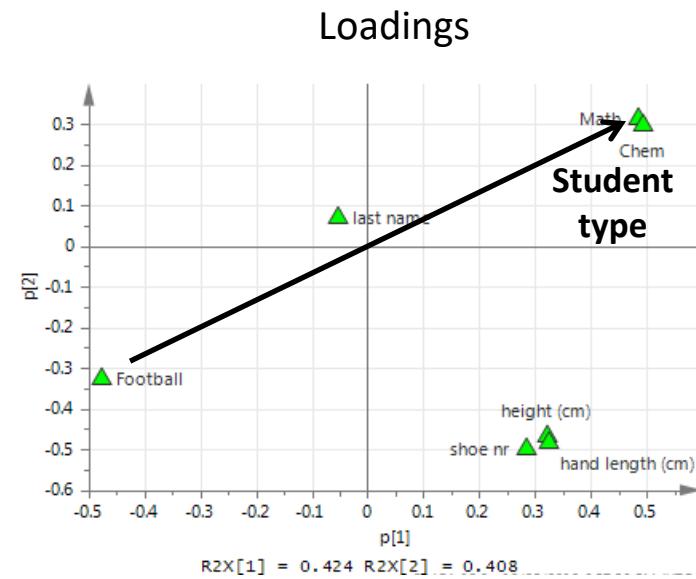
Yellow points are the observed values. Blue points are their PC approximations.

Projected locations on the model (line, plane, or hyperplane) are given by the *scores* (t)

PCA is an unsupervised technique. No assumptions are made about the samples. Adequately labeling the samples (and coloring them) helps us to visualize trends.



The "Good" and "Bad" students are separated

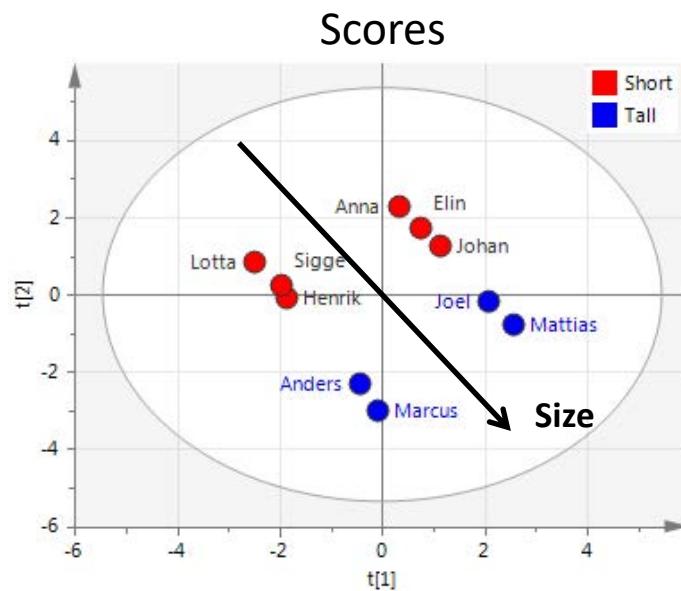


The variables that correlate with each other are observed

The variables that are important in the definition of a "good" or "bad" student may be understood from comparing scores and loadings

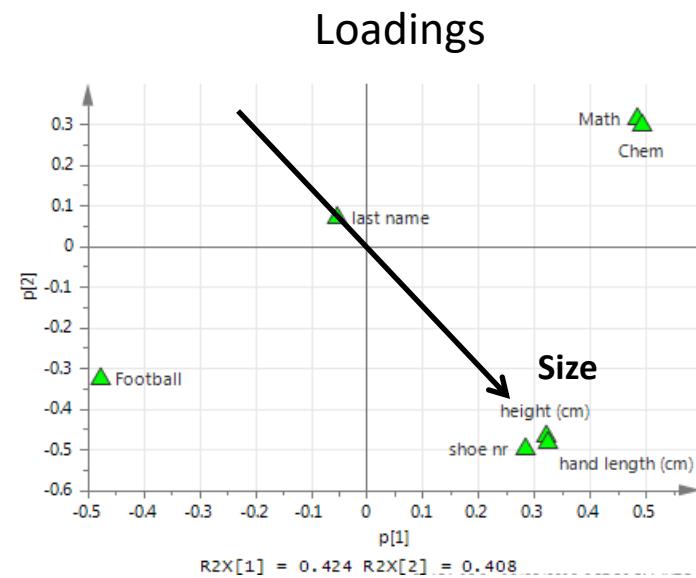
Example PCA students performance (PC1 x PC2)

Now let's color the same plot according to "Short" and "Tall"



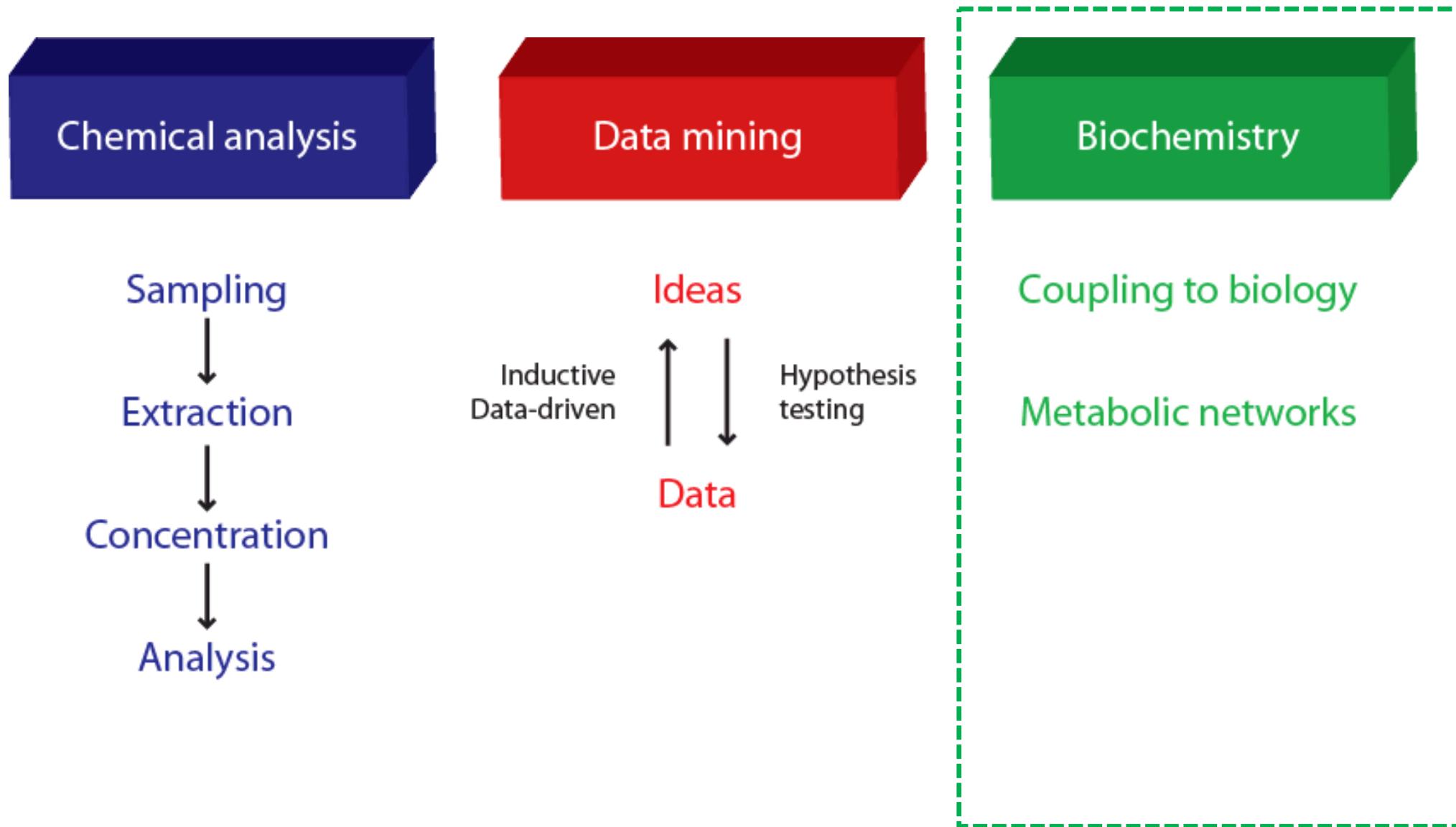
The "Short" and "Tall" students are separated

The variables that are important in the definition of a "Short" or "Tall" student may be understood from comparing scores and loadings

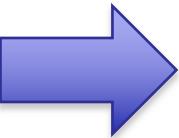
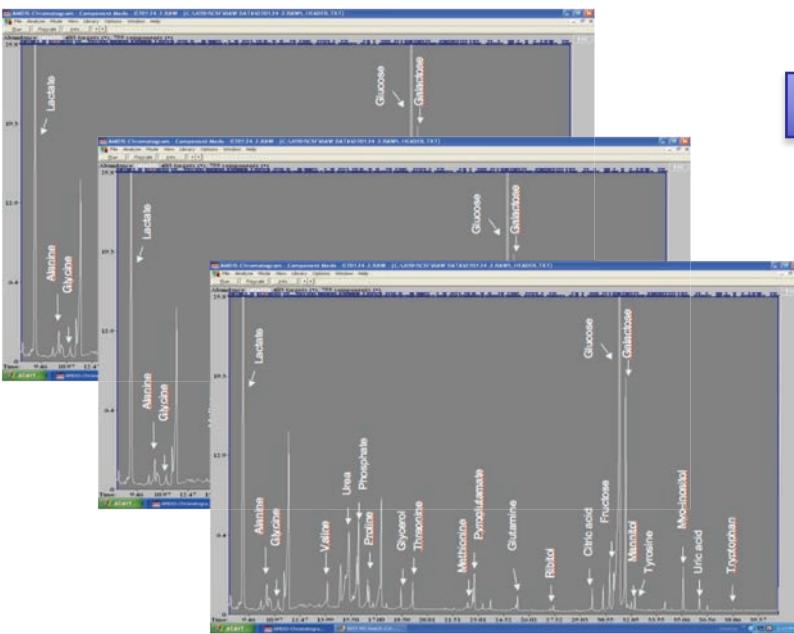
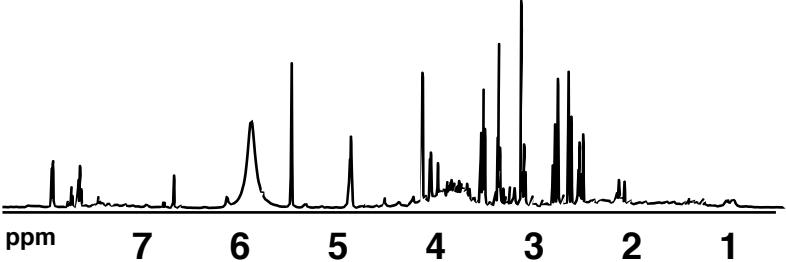


The variables that correlate with each other are observed

Metabolomics workflow



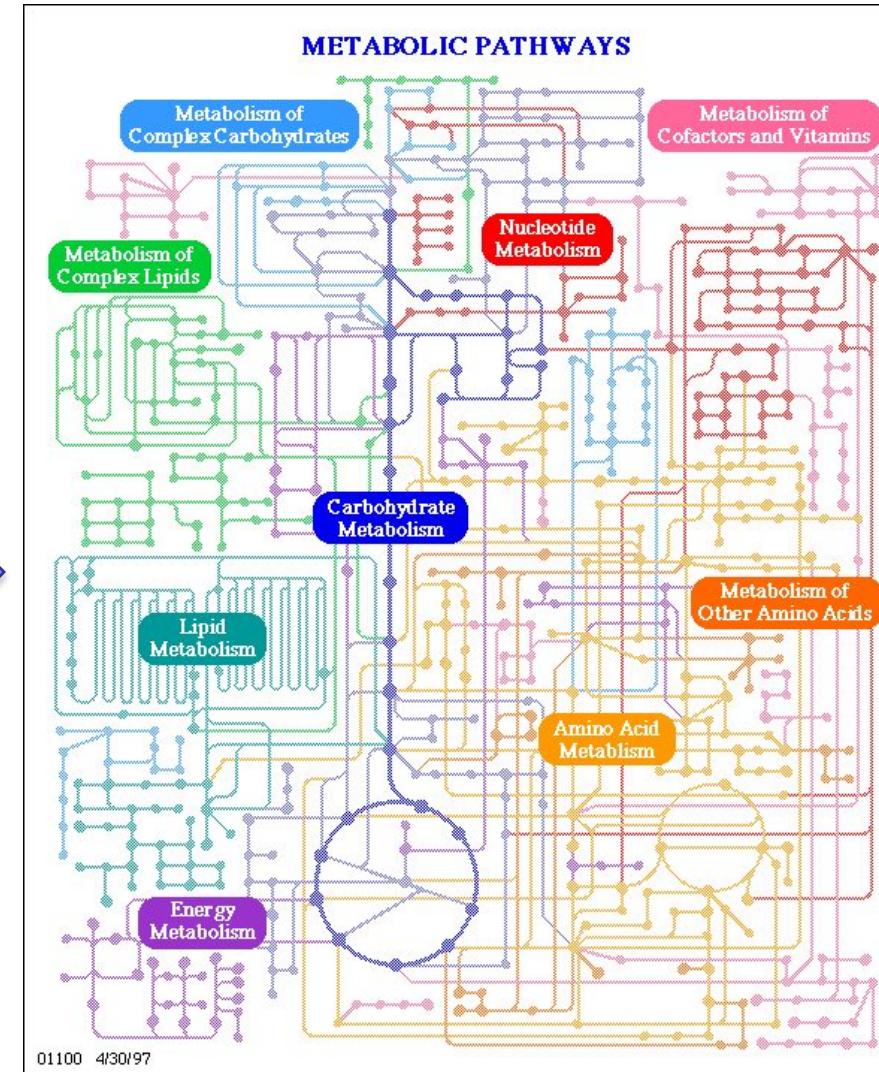
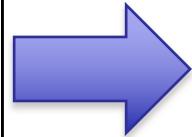
From Spectra to Lists



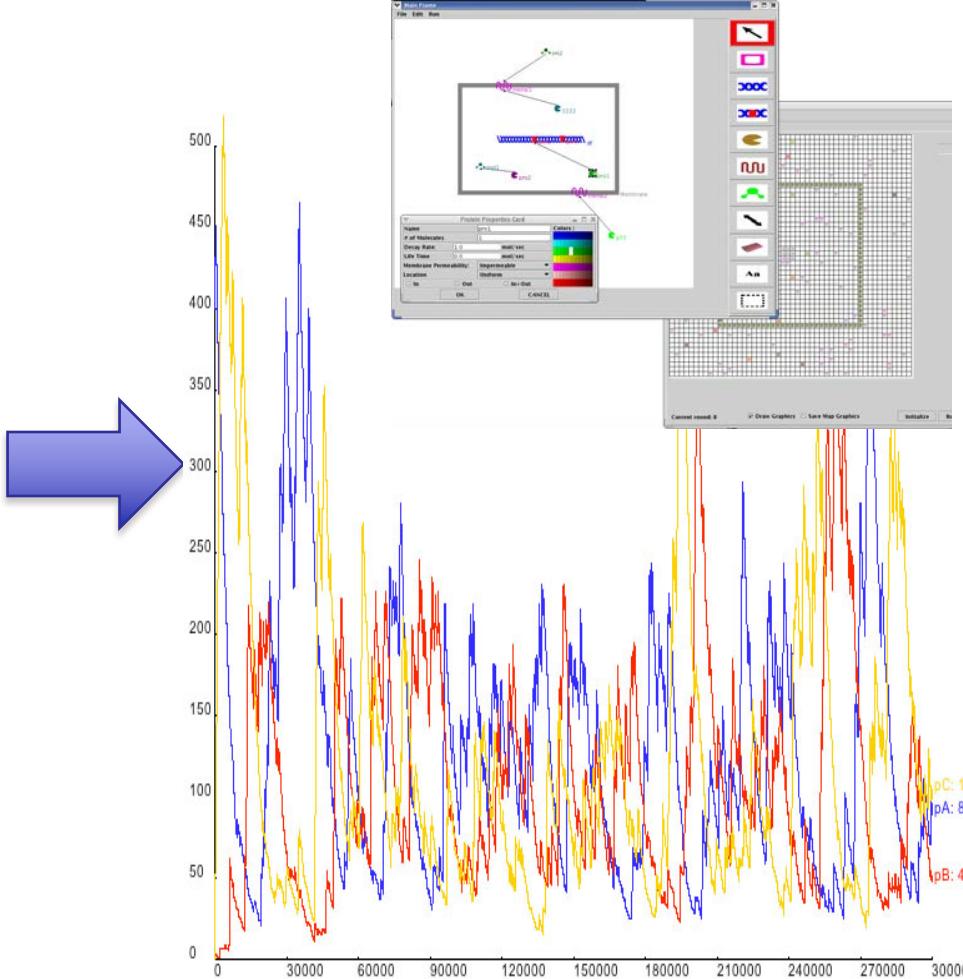
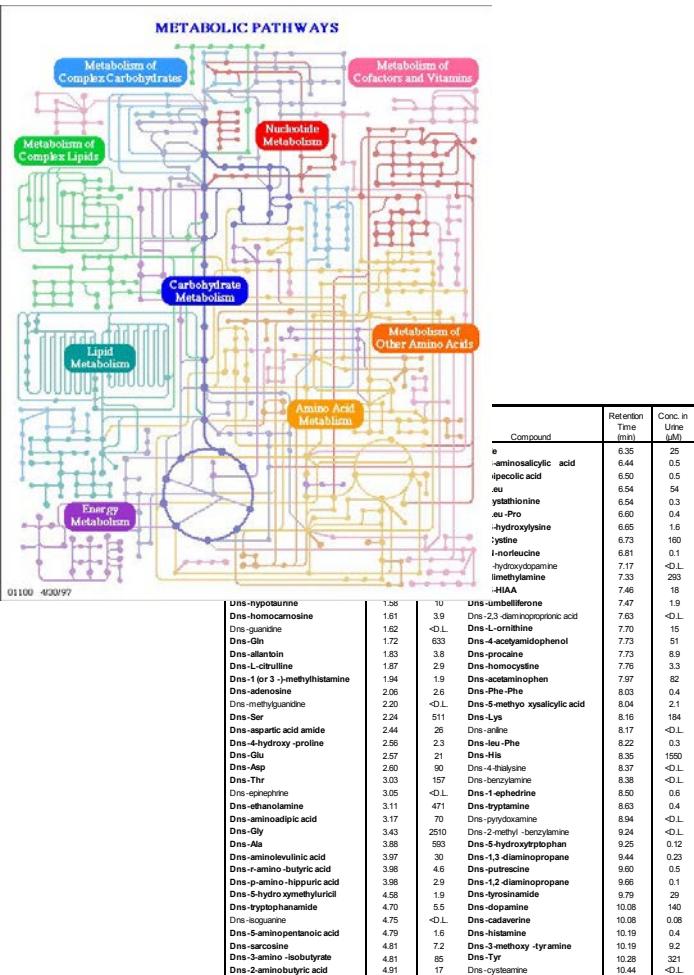
Compound	Retention Time (min)	Conc. in Urine (μM)	Compound	Retention Time (min)	Conc. in Urine (μM)
Dns-o-phospho-L-serine	0.92	<D.L.	Dns-Ile	6.35	25
Dns-o-phospho-L-tyrosine	0.95	<D.L.	Dns-3-aminosalicylic acid	6.44	0.5
Dns-adenosine monophosphate	0.99	<D.L.	Dns-piperolic acid	6.50	0.5
Dns-o-phosphoethanolamine	1.06	16	Dns-Leu	6.54	54
Dns-glucosamine	1.06	22	Dns-cystathione	6.54	0.3
Dns-o-phospho-L-threonine	1.09	<D.L.	Dns-Leu-Pro	6.60	0.4
Dns-6-dimethylaminopurine	1.20	<D.L.	Dns-5-hydroxylysine	6.65	1.6
Dns-3-methyl-histidine	1.22	80	Dns-Cysteine	6.73	160
Dns-taurine	1.25	834	Dns-N-norleucine	6.81	0.1
Dns-carnosine	1.34	28	Dns-5-hydroxydopamine	7.17	<D.L.
Dns-Arg	1.53	36	Dns-dimethylamine	7.33	293
Dns-Asn	1.55	133	Dns-5-HIAA	7.46	18
Dns-hypotaurine	1.58	10	Dns-umbelliferone	7.47	1.9
Dns-homocarnosine	1.61	3.9	Dns-2,3-diaminopropionic acid	7.63	<D.L.
Dns-guanidine	1.62	<D.L.	Dns-L-ornithine	7.70	15
Dns-Gln	1.72	633	Dns-4-acetylamidophenol	7.73	51
Dns-allantoin	1.83	3.8	Dns-procaine	7.73	8.9
Dns-L-citrulline	1.87	2.9	Dns-homocystine	7.76	3.3
Dns-1(or 3)-methylhistamine	1.94	1.9	Dns-acetaminophen	7.97	82
Dns-adenosine	2.06	2.6	Dns-Phe-Phe	8.03	0.4
Dns-methylguanidine	2.20	<D.L.	Dns-5-methoxy xysalicylic acid	8.04	2.1
Dns-Ser	2.24	511	Dns-Lys	8.16	184
Dns-aspartic acid amide	2.44	26	Dns-aniline	8.17	<D.L.
Dns-4-hydroxy-proline	2.56	2.3	Dns-leu-Phe	8.22	0.3
Dns-Glu	2.57	21	Dns-His	8.35	1550
Dns-Asp	2.60	90	Dns-4-thialysine	8.37	<D.L.
Dns-Thr	3.03	157	Dns-benzylamine	8.38	<D.L.
Dns-epinephrine	3.05	<D.L.	Dns-1-ephedrine	8.50	0.6
Dns-ethanolamine	3.11	471	Dns-tryptamine	8.63	0.4
Dns-aminoacidipic acid	3.17	70	Dns-pyroxidine	8.94	<D.L.
Dns-Gly	3.43	2510	Dns-2-methyl-benzylamine	9.24	<D.L.
Dns-Ala	3.88	593	Dns-5-hydroxytryptophan	9.25	0.12
Dns-aminolevulinic acid	3.97	30	Dns-1,3-diaminopropane	9.44	0.23
Dns-r-amino-butrylic acid	3.98	4.6	Dns-purtescine	9.60	0.5
Dns-p-amino-hippuric acid	3.98	2.9	Dns-1,2-diaminopropane	9.66	0.1
Dns-5-hydroxyethyluricil	4.58	1.9	Dns-tyrosinamide	9.79	29
Dns-tryptophanamide	4.70	5.5	Dns-dopamine	10.08	140
Dns-isoguanine	4.75	<D.L.	Dns-cadaverine	10.08	0.08
Dns-5-aminopentanoic acid	4.79	1.6	Dns-histamine	10.19	0.4
Dns-sarcosine	4.81	7.2	Dns-3-methoxy-tyramine	10.19	9.2
Dns-3-amino-isobutyrate	4.81	85	Dns-Tyr	10.28	321
Dns-2-aminobutyric acid	4.91	17	Dns-cysteamine	10.44	<D.L.

From Lists to Pathways

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Dns-sarcosine	4.81	7.2	Dns-3-methoxy -tyramine	10.19	9.2
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Dns-2-aminobutyric acid	4.91	17	Dns-cysteamine	10.44	<D.L.



From Pathways & Lists to Models & Biomarkers



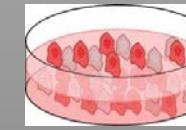
Metabolomics application in life sciences



Food application



Biotechnology



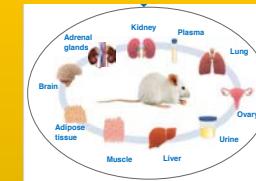
Metabolomics
Technologies



Plant & Agriculture



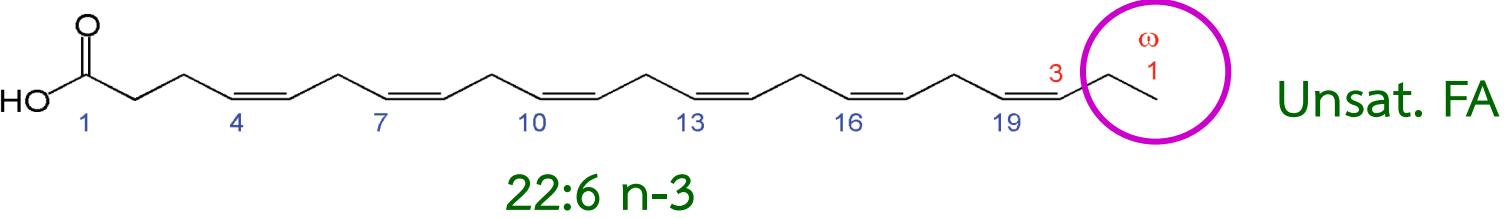
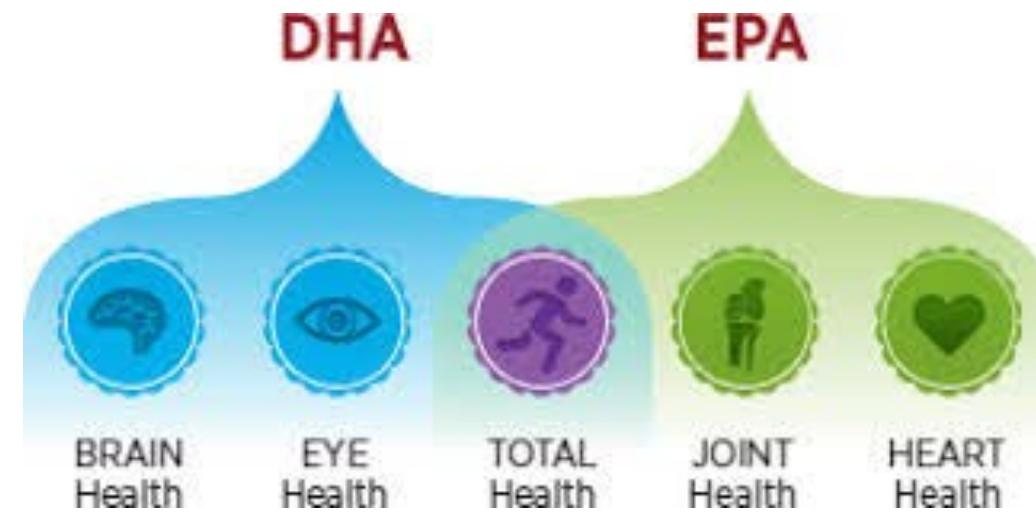
Medicine



Example I Food



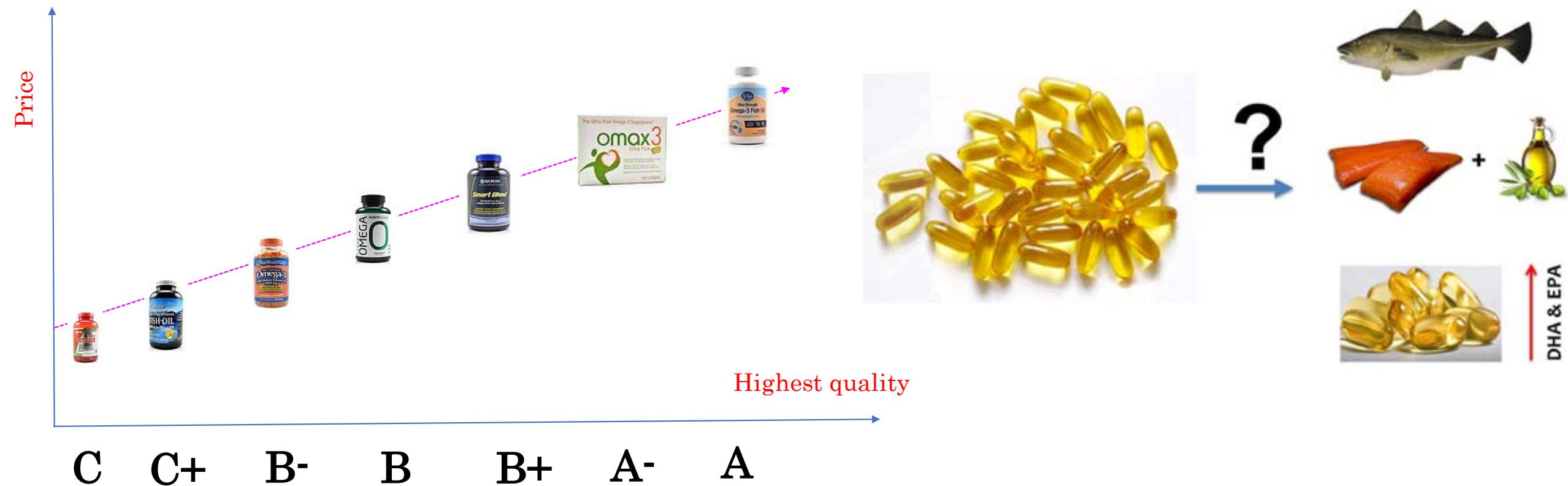
Greenland Eskimos
Dyerberg et al (1978)



Dyerberg et al., (1978) The lancet 312 : 117-119

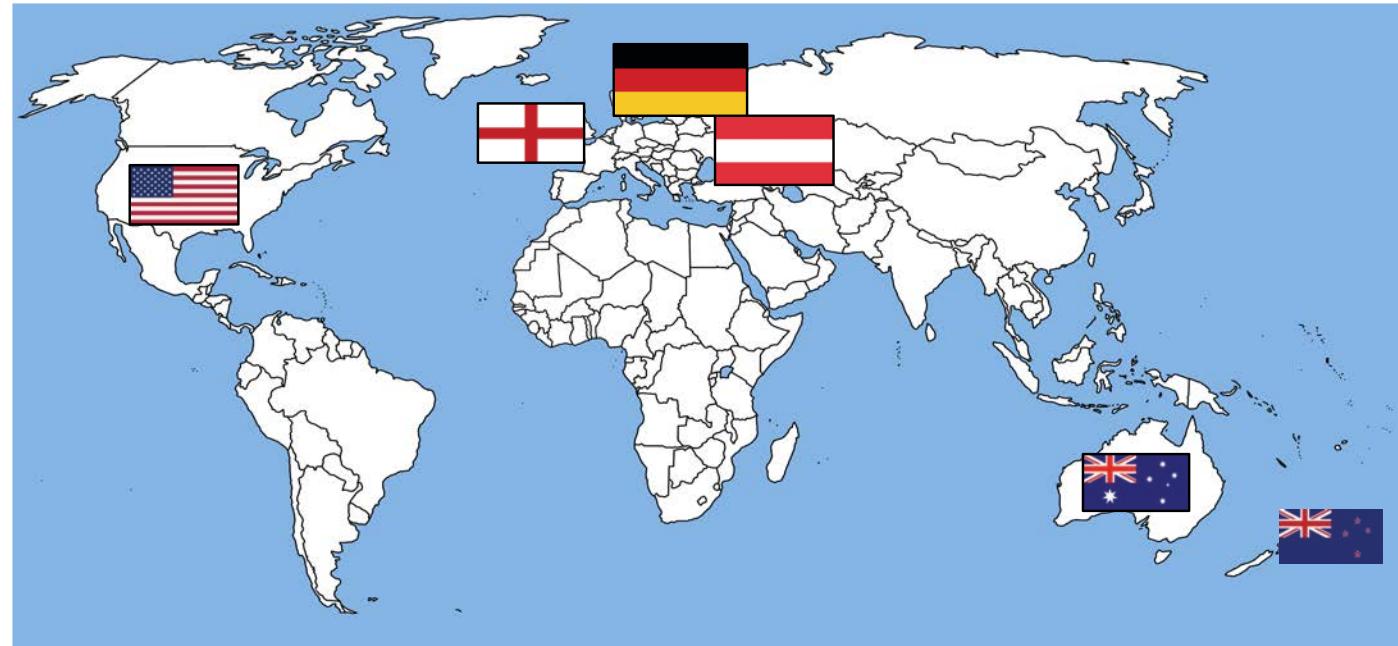
Research Question

Type/ grade of fish oil supplements

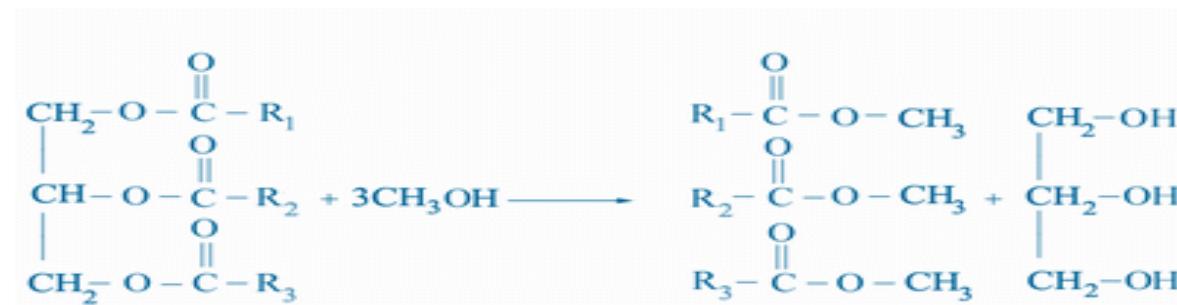


Fish oil supplement samples

Group	Type of fish oil	Number of sample	Code
1	Fish oil enriched	8	FOE
2	Pure fish oil	3	PFO
3	Salmon oil	4	SMO
4	Cod liver oil	6	CLO
5	Krill oil	1	KO
6	Fish oil + plant oil	3	FO+SO



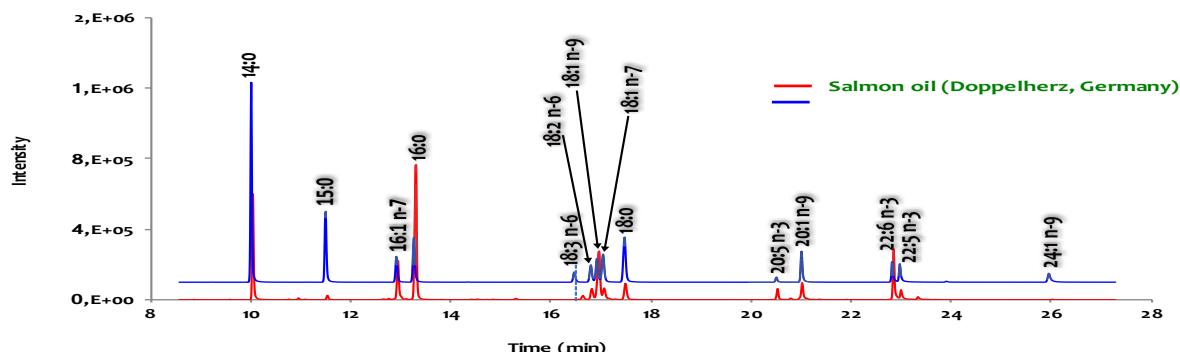
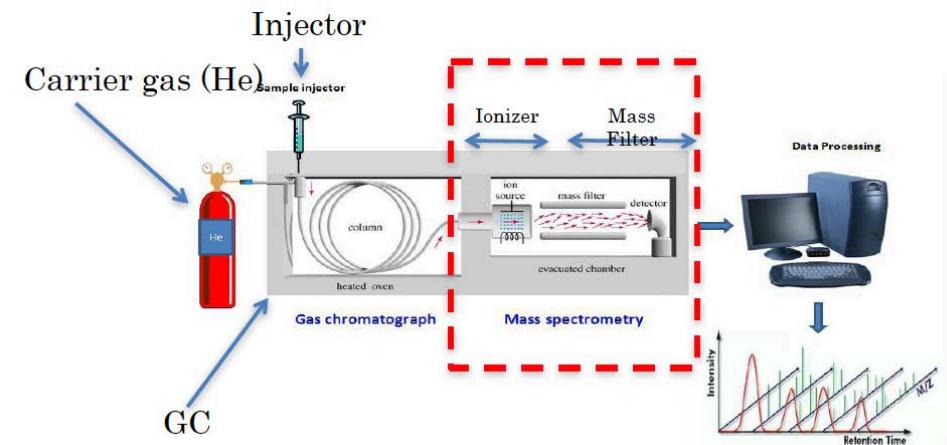
Total fatty acid analysis by GC-MS



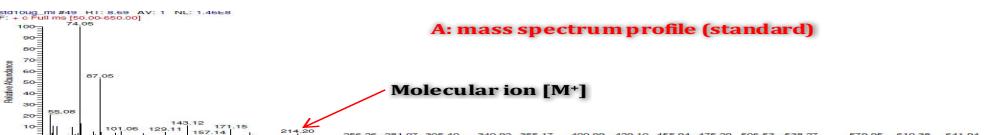
TAG

FAMEs

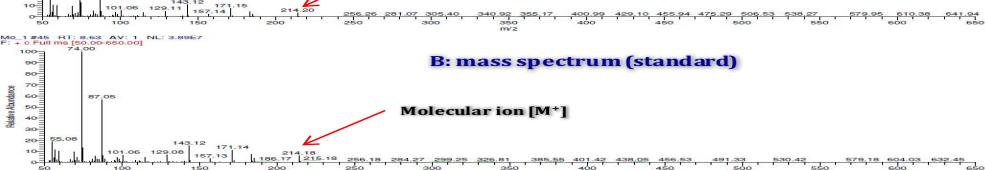
Glycerol



A: mass spectrum profile (standard)

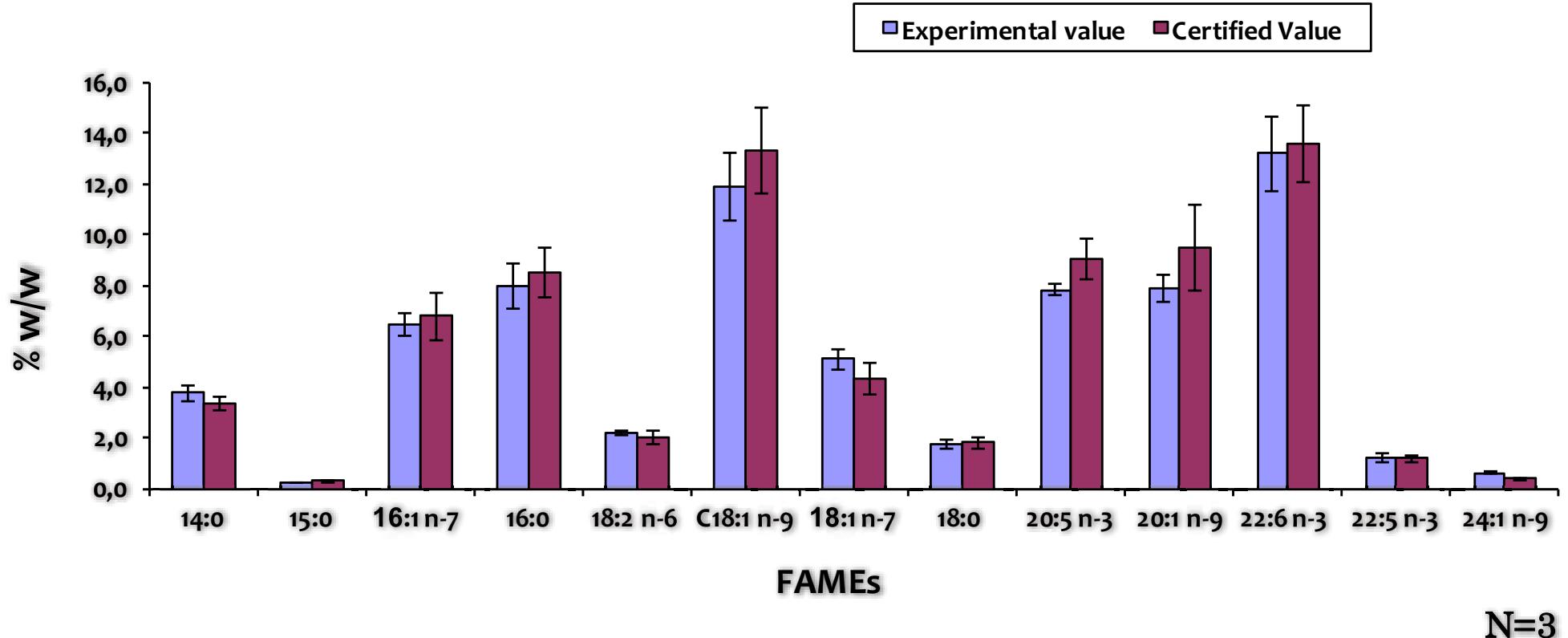


Molecular ion [M^+]



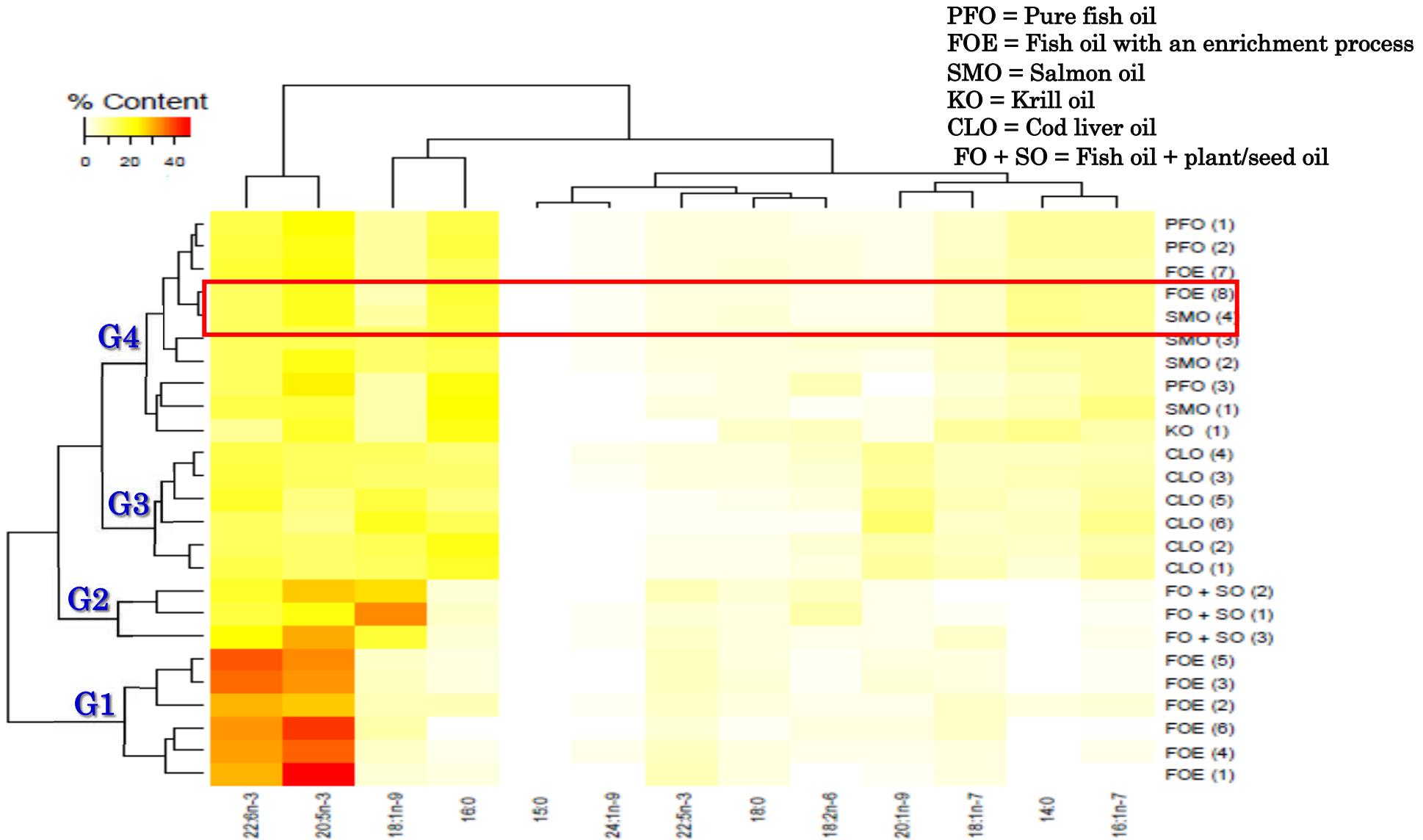
Molecular ion [M^+]

Test the method



SRM from National Institute of Standards & Technology, USA

Hierarchical clustering algorithm of fatty acid profiles



Example 2

ARTICLE

doi:10.1038/nature09922

Gut flora metabolism of phosphatidylcholine promotes cardiovascular disease

Zeneng Wang^{1,2}, Elizabeth Klipfell^{1,2}, Brian J. Bennett³, Robert Koeth¹, Bruce S. Levison^{1,2}, Brandon DuGar¹, Ariel E. Feldstein^{1,2}, Earl B. Britt^{1,2}, Xiaoming Fu^{1,2}, Yoon-Mi Chung^{1,2}, Yuping Wu⁴, Phil Schauer⁵, Jonathan D. Smith^{1,6}, Hooman Allayee⁷, W. H. Wilson Tang^{1,2,6}, Joseph A. DiDonato^{1,2}, Aldons J. Lusis³ & Stanley L. Hazen^{1,2,6}

Trimethylamine N-oxide (TMAO) and atherosclerosis

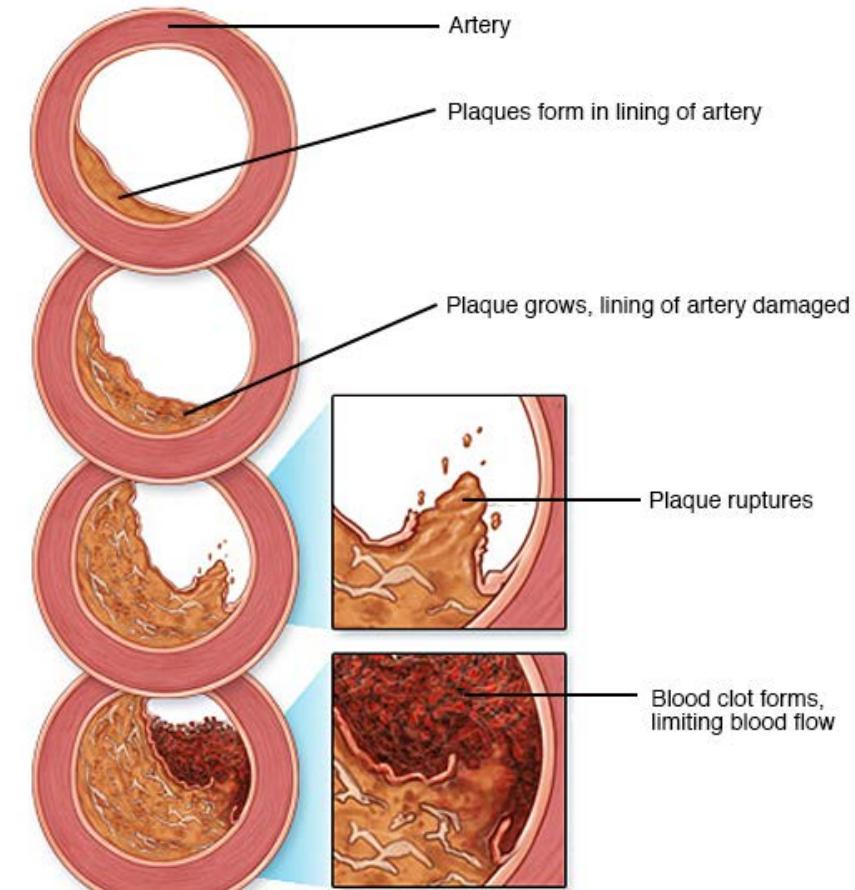
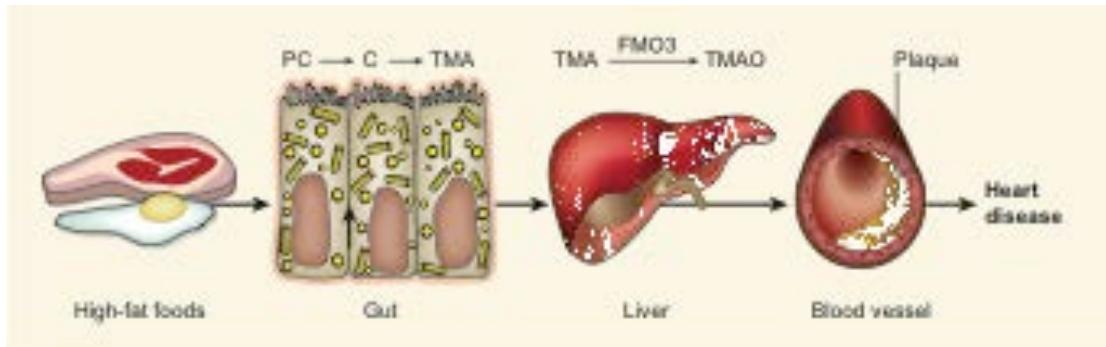
Atherosclerosis

A disease of the arteries characterized by the deposition of fatty material on their inner walls- Normally reattributed from bad gene and high cholesterol



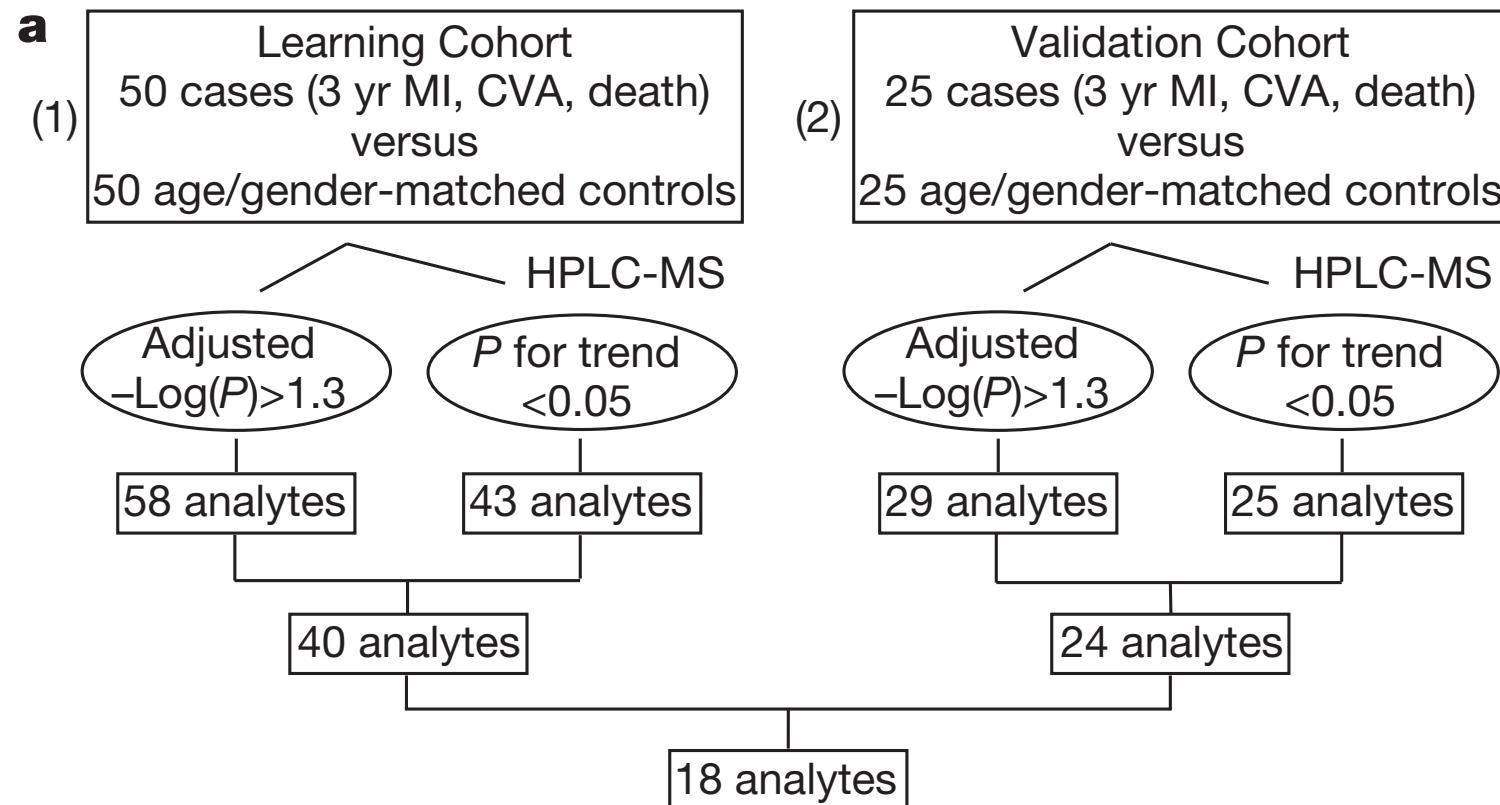
Stanley L. Hazen

Cleveland Clinic Main Campus



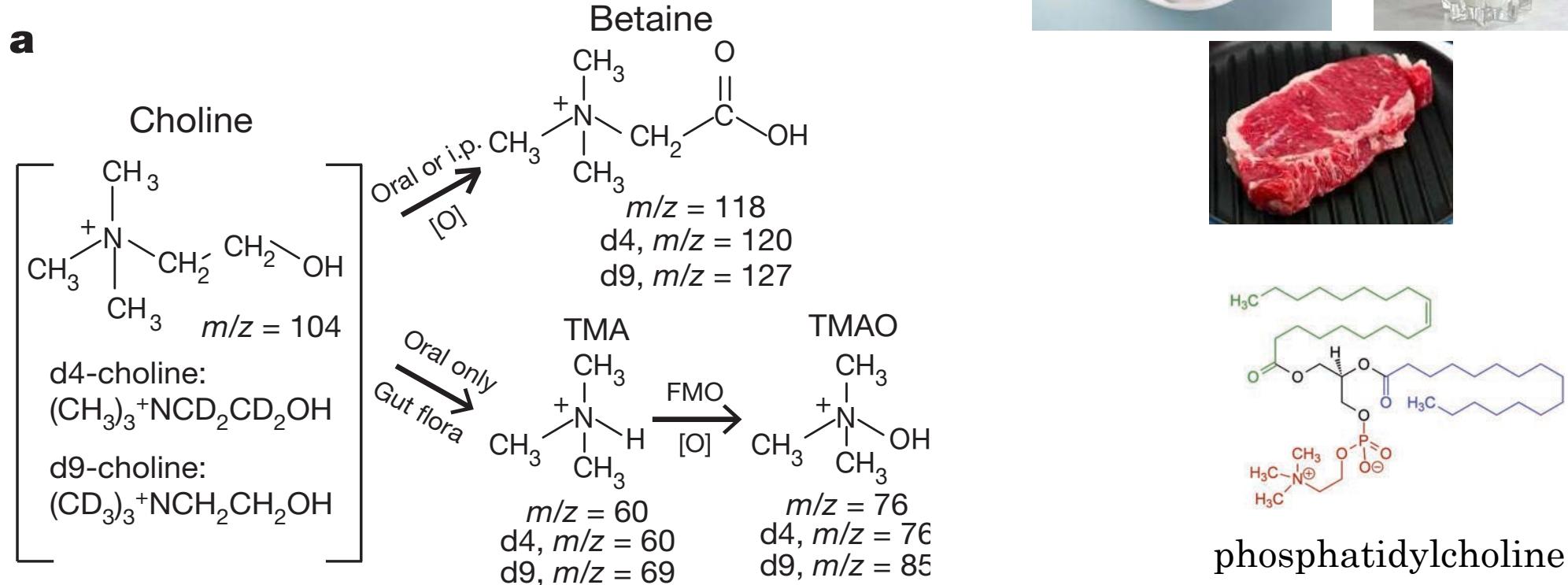
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1. Discover metabolite biomarkers in plasma to predict CVD
2. Learning cohort:
 - (A) stable patients and subsequently experienced heart attack (myocardial infarction), stroke or death
 - (B) A group of age- and gender-matched subjects who did not
3. LC-MS provided <2000 features → 40 metabolites identified as biomarkers
4. An independent cohort identified 18 were identified in both cohorts
5. *m/z 76, 104 and 118* → top candidates ($P < 0.001$)
6. Structure identification



What are m/z 76, 104 and 118 ?

- NMR, LC-MS/MS and GC-MS
- m/z 76 = TMAO (***Trimethylamine N-oxide***)



B

Pre-treatment of antibiotics of
The gut micro flora



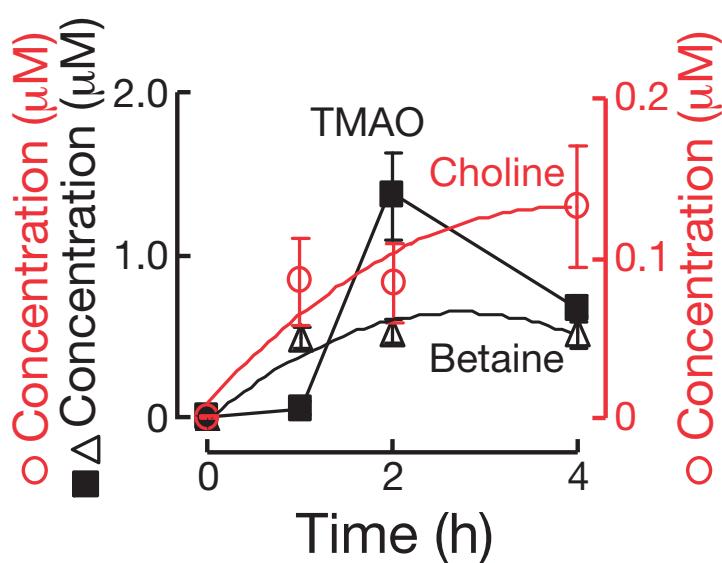
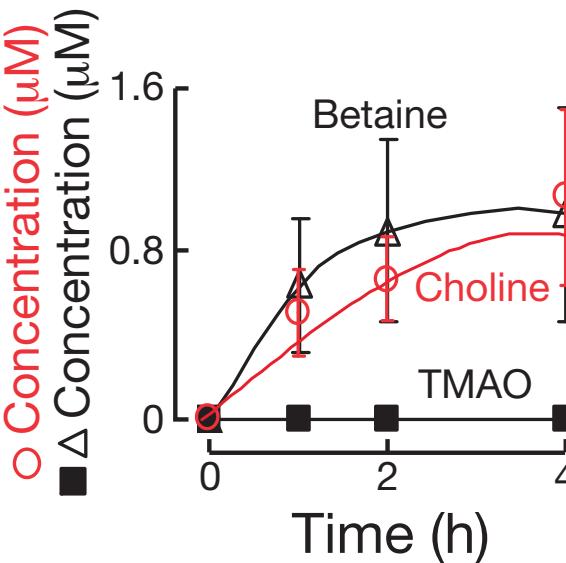
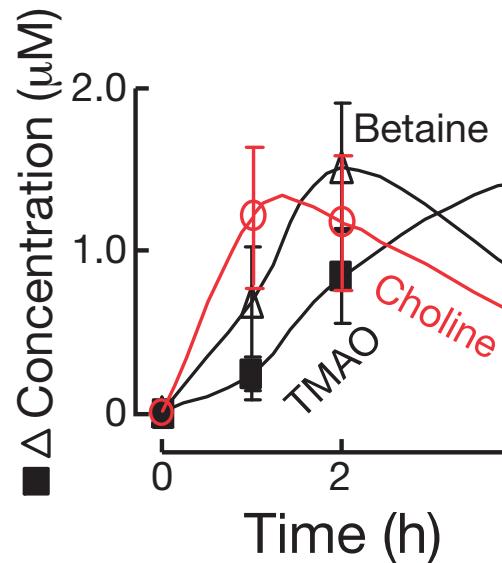
Fed with egg-yolk PC

C d9-DPPC gavage

Pre-antibiotics Supresion of
microflora

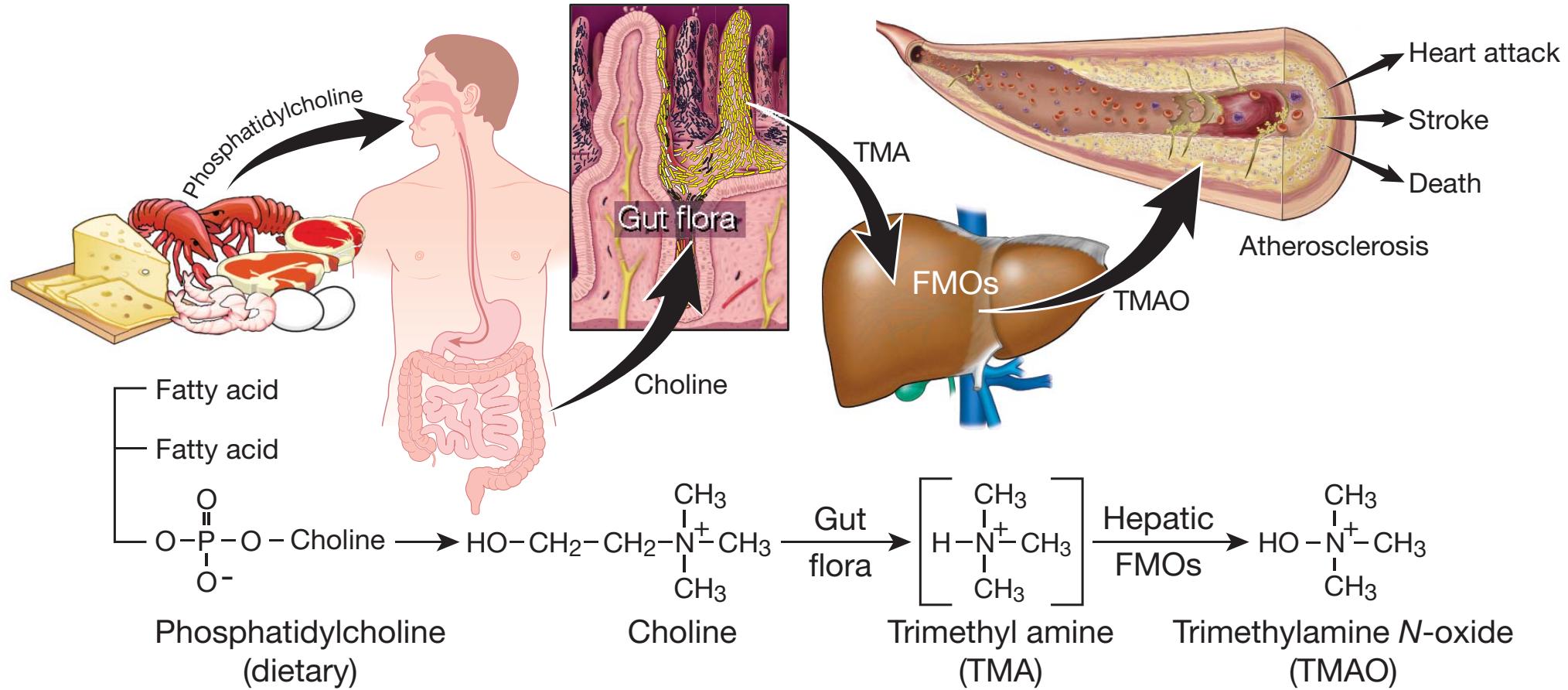
Acquisition of
microflora

Post-antibiotics Conventionalized



d9-TMAO production after oral d9-DPPC administration in mice, following suppression of gut flora with antibiotics (3 weeks), and then following placement (4 weeks) into conventional cages with non-sterile mice ('conventionalized'). Data are presented as mean \pm standard error (s.e.) from four independent replicates.

Gut-flora-dependent metabolism of dietary PC and atherosclerosis



Conclusions

1. Introduction to Metabolomics

- Metabolomics ?
- Relation to other -omics → systems biology

2. Metabolomics technologies

- Wet metabolomics
- Dry metabolomics

3. Metabolomics in precision medicine